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Strategic decision support system (DSS) for deregulated electricity industry

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Strategic decision support system (DSS) for deregulated electricity industry

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CHAPTER 1. INTRODUCTION

The electric power industry has been given the task of deregulating. This means they must change from a monopolistic stance on business, with guaranteed return on investment, to a competitive open market. Reaching the plateau of an open electricity market with more efficiency and lower prices is proving to be a difficult feat. Many models have been proposed and studied on how to change these vertically integrated utility companies, with an obligation to supply electricity to the customers, into separate generating, transmission, and service companies. To date, restructuring proposals for the electric power industry have primarily focused on the wholesale electricity market. In this market, electricity is produced by generating companies (GENCO) from existing capacity and sold either to other generators or to some form of energy service provider. The energy service providers subsequently resell the electricity to household, industry, or commercial users in a retail market.

The old "regulated" system relied on privately initiated bilateral contracts to exchange amounts of energy. To make and exchange the contracts more freely, the need for independent administrators in the electricity market arose and is being used in many of the deregulated areas of the country. ISO (Independent System Operators) and ICA (Independent Contract Administrators) were developed as final arbitrators and clearinghouses for the buying and selling of electricity. The clearinghouse double auction exchanges required participants to simultaneously submit a price and quantity for electricity in each round of the auction. The auction then picks the price by using either a discriminatory or uniform method. These exchanges can have the authority to refuse contracts between participants due to physical transmission conflicts, credit problems, quality concerns, or potentially unethical practices. One unethical practice is to "game" an auction mechanism, i.e. to behave opportunistically within the limits set by the auction protocols in an attempt to increase their individual gains to trade. This could easily include: some sort of price setting, making contracts to artificially congest a section of the transmission grid to drive up the price in that area, or misrepresenting their true willingness to pay. The manner in which the clearinghouse protocols are structured can have drastic affects on who can be given an unfair advantage over other users. A large amount of research and trials are needed to identify the protocols and circumstances that create these unfair advantages. This can be difficult to predict in advance using standard analytical tools. Therefore, computational experiments seem to be more useful.

Successful operation and bidding in the competitive electricity marketplace requires well-planned strategies. The appropriate strategy is dependent on the state of the system. The state of the system can be predicted with a certain amount of accuracy. Traditional data analysis techniques can be time consuming. Techniques that quickly analyze the data can assist in forecasting price and demand, and in identifying the present state of the market, which should help the savvy trader in reacting intelligently to the market before its competitors.

This thesis will show the value of the information provided by knowing the advantages of strategic auction protocols, the competition's strengths through careful modeling, load forecasting, decision tree analysis with probability theory, risk analysis, and the financial instruments to hedge that risk. Using these tools in combination will help maximize profit while minimizing risk and losses. With the competition expanding, companies in the energy industry will need to utilize all important information and disregard extraneous data to make the right long term planning decisions. Even everyday trading of electricity will have to utilize such risk reduction and system analysis techniques in order to keep the company away from financial difficulties. These analysis processes can be developed into making financial decision for a newly deregulated energy company.

CHAPTER 2. LITERATURE REVIEW

Successful operation and bidding in the competitive electricity marketplace requires well-planned strategies. The appropriate strategy is dependent on the state of the system. Much data (including time series) is available, and a proper analysis of this data can provide insight in choosing the right strategies. Traditional data analysis techniques can be time consuming. Techniques that quickly analyze the data can assist in forecasting price and demand and identifying the present state of the market, which should help the savvy trader in reacting intelligently to the market before its competitors. Advanced data analysis techniques may reveal patterns in the data that may be very helpful in forecasting demand or price [22]. Artificial Neural Networks have been studied and are commonly employed for short-term load and price forecasting.

Artificial Neural Networks (ANN)

The Artificial Neural Networks (ANN) is an artificial intelligence program to interpret the correlation of a set of inputs into a projected output. The idea behind this technique came from the theory of how researchers think the human brain recognizes and retains events and objects in its memory. The brain is an electrochemical storage device that utilizes its very structure to learn information. It's filled with 100 billion neurons, or simple processing elements that give off brief electrical pulses when they are sufficiently excited. "As a person is exposed to events, his sensory nerves cause neurons in the brain to be excited and pulse. If this pulsing is frequent enough, the interconnection strength between neurons new information is added to the memory" [34]. Thus as a person learns, these weighted connections are combined to reconstruct the event for future reference. This is essentially the way the human brain structure changes, and the way an ANN is programmed. The ANN is a mathematical representation of these weighted connections between the neurons. Figure 2.1 depicts an artificial neuron (Perceptron). This network, and its knowledge of how the inputs affect the output, can be used for a wide range of applications but the most commonly used purpose is prediction or forecasting future output events.

Feedforward networks

The most common type of Artificial Neural Network is the Feedforward network depicted in Figure 2.2. These networks may have more than one layer of neurons connected to each other through more weighted connections and transfer functions. The transfer functions, or activation functions, are used to fine-tune the output. The output of a neuron is high if the summation of the inputs is greater than some threshold value. If it is less than the

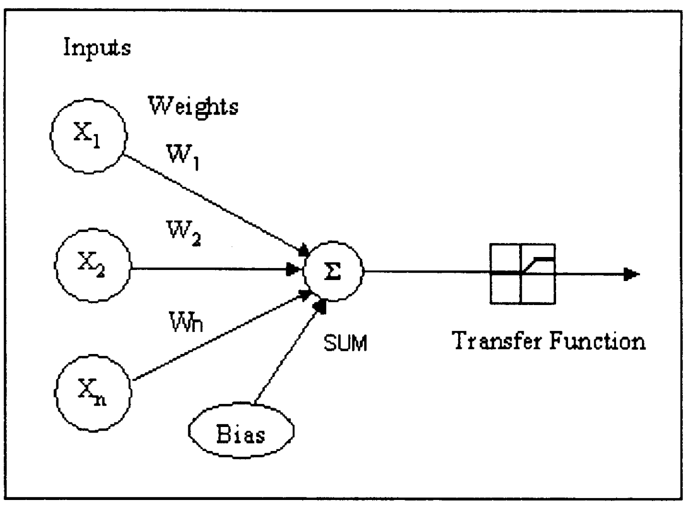

Figure 2.1 ANN neuron or perceptron.

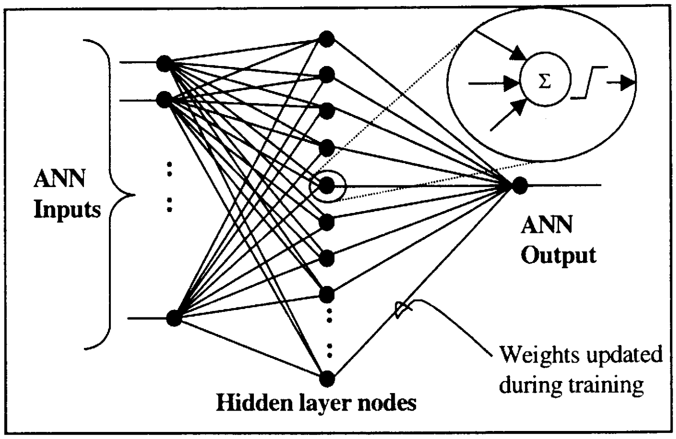

Figure 2.2 Feedforward ANN.

threshold the output becomes low. The output of the first layer of neurons are the inputs to the hidden layers, or the unobserved layers between the input layer and output layer of neurons. ANN often have more than one hidden layer to solve non-linear problems. Figure 2.2 is an example of a network with one hidden layer. The transfer functions are typically a combination of the following: linear threshold, sigmoid, hyperbolic tangent, gaussian, and step functions. The sigmoid can be expressed as:

$$F(x) = \frac{1}{1 + e^{-cx}}$$

where c is a constant. In that case, the output may be somewhere between high (1) and low (0) depending on the strength of the inputs. The sigmoid is typically used as a "squashing" function so the output depends smoothly on the activation [13]. A linear transfer function and a sigmoid are shown in Figure 2.3. The linear transfer function can be considered a linear approximation of the sigmoid for semi-linear problems. For hidden layer neurons with the sigmoid transfer function, the output is:

$$Y_j = \frac{1}{1 + exp(-\sum_{i=1}^{n} W_{ij} X_i)}$$

where Y_j is the output of the jth hidden layer neuron, $j = 1, \ldots ,h$, and X_i represents the ith input connected to this hidden node via W_{ij} with $i = 1, \ldots ,n$.

Basic training of the NN

Before the ANN can forecast it has to be trained to recognize patterns in the input data as it relates to the output. As inputs are exposed to the network, the ANN changes the weights of each input to match or settle within a given error range of an expected output. The error range for the network is defined as the sum-squared-error over a set of input-output training pairs. As the error is reduced, the adjustment of the interconnection weights is less aggressive. The most common training algorithm for feedforward networks is a gradient decent technique known as back-propagation. This iterative method is a "blame-assigning" algorithm that changes a weight based on that interconnection's contribution to the output error [34].

It is possible to over-train an ANN, meaning that the network will "memorize" the training data set, and would not perform well when presented with a new set of test inputs. One way to avoid over-training is to keep track of the performance on the test set of data. A

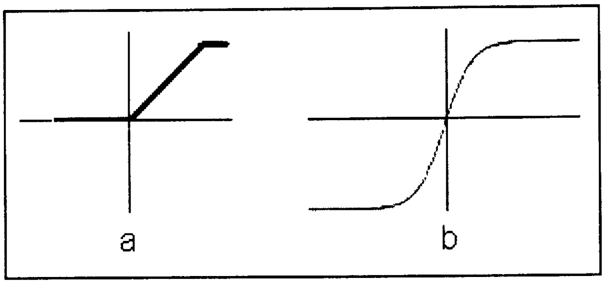

Figure 2.3 (a) Linear threshold and (b) Sigmoid function.

method proposed by Hecht-Nielsen says the weights should be adjusted only on the basis of the training set, but the error should be monitored on the test set [20]. The training should be stopped when the magnitude of the error starts to increase after a minimum has been reached. Many iterations help eliminate random fluctuations. To keep the generalization capabilities of the ANN, injecting some noise into the training set is a useful technique [20].

Other ANN frameworks

ANN research is constantly changing to adapt to different problems. ANN research has included varying interconnection schemes between neurons, altering neuron transfer functions, experimenting with mathematical techniques to determine the interconnection strengths that optimize the system, and determine where the networks are best suited for application [34]. There are many possible variations to the basic design of the ANN. Other more advanced and widely studied ANN schemes are: the Hopfield Network, Self-Organizing Networks, Adaptive Resonance Theory (APT), and Stacked Generalization Neural Networks (SG).

Hopfield network

The neurons are characterized by a bipolar of binary output and a threshold transfer function. Hopfield networks are fully connected; implying the output of each neuron is fed back to the input of each other neuron via weighted symmetric weighted connections. The neurons are selected for update according to a probability distribution [34] [20] [12].

Kohonen self-organizing maps (SOM)

SOM consist of an input layer and a Kohonen layer. They can be trained using supervised and unsupervised learning algorithms. The key difference of this ANN is the output of the SOM comes from the Kohonen layer instead of the output neurons. The Kohonen layer simply selects the Kohonen neuron with the highest activation level and assigns its neuron number as the output. This architecture makes SOMs excellent classifiers. Although the number of neurons in the Kohonen layer indicates the number of patterns that a SOM will be able to recognize [35].

Adaptive resonance theory (ART)

ART was to learn without having to erase (forget) or to substantially erase earlier learned patterns. It operates as an unsupervised self-organized network. The ART network consists of the following: a Comparison layer, a Recognition layer (which is interconnected), two gain elements connected to each of the two layers, and a Reset element which evaluates the output of the comparison layer to a given tolerance value [12]. The ART was designed to be a classifier and not a forecasting network.

Stacked generalization neural networks (SG)

First introduced by David Wolpert, SG improves the ANN model performance. SG uses a number of different ANN models. These models are compared, and the resulting information is used in the stacking process, which combines the models and provides error estimates. The additional feature of allowing these networks to have different input variable subspace vectors was added because of differences in individual model response. "Thus, each model's response expresses different features of the process to be modeled, providing a more complete representation of the overall process. This ability to have different input vectors improves overall accuracy" [1].

Short Term Load Forecasting

The ability to accurately forecast the demand of a generating company requires the appropriate forecasting technique to analyze the optimal set of data. Forecasting errors can cost deregulated energy companies millions of dollars in fuel contracts or bilateral contracts. Inaccurate forecasting can cause very expensive mistakes in contract bidding and reserve estimations. Because of the variety of techniques and possible data sets, a great deal of research has gone into the analysis of which techniques and exactly how much data is needed to forecast with an acceptable level of accuracy.. Some of the older techniques are: linear regression, moving averages, exponentially weighted averages, weighted moving averages, and auto-regressive moving averages (ARMA). These are easy and fast techniques, but lack in the precision and flexibility needed for nonlinear problem solving. Since ANN have shown the most promise in the field of forecasting, researchers are constantly developing new techniques to: reduce the amount of computation time, increase the training speed of the ANN, or increase the accuracy of the predictions from an ANN.

ANN STLF

Some ANN are simply better suited to optimization or classification than forecasting. The most established method for STLF (short term load forecasting) is multi-layer feed-forward back propagation type networks [18] [29] [9] [7]. Most of the current research has been amending these networks to get better performance at short and long term forecasting. A few of the recent ideas to adjust the typical networks are: using a pre-filter for the input data, using better methods to calculate error, and adding noise to the input data to better handle large variations in the test data sets. Some of the more radical modifications under research are: hybrids of NN and other linear estimators [31], parallel NN and fuzzy-expert systems [28], Wavelet NN [2], and multiple SOMs working together [7]. These new techniques are interesting but are not significantly better than the multi-layer perceptrons.

M. H. Choueiki in [9] looked at the common ANN factors applied to STLF and attempted to find a "quasi-optimal" network. They compiled a list of the different configurations presently used by STL forecasters and tested them against each other in many combinations. The factors they tested are listed in Table 2.1. "The RMSE testing results range between 3.87% for the worst of the 64 experimental sessions and 2.01% for the best sessions." The authors contrived a set of rules for building a "quasi-optimal" neural network to solve the STLF problem. The rules are:

1.The sigmoid function should be used as the transfer function in the output layer.

2.The sinusoid function should be used as the transfer function in the hidden layers.

3.One hidden layer is sufficient for solving the STLF problem, and the Cascade Correlation algorithm (where outer layers of hidden nodes are successively added to a steadily growing layered NN until performance is judged adequate) should be used to determine how many nodes are necessary.

4.The cumulative backpropagation rule should be used for updating the weights during training.

5. The Concurrent Descent method (terminates training when the RMSE measured on an independent data set (not the training set) is minimized while the RMSE measured on the training set is still declining) should be used for terminating the training phase.

6. A recurrent neural network should be used.

7. The network should be re-trained monthly, and used for forecasting by replacing the weights of the oldest months data with the most recent month of data

8. Training data should include information on load behavior during normal as well as abnormal weather conditions.

9. A good starting point for the learning and momentum rates are the learning schedules described in [8].

10. Noise should be added to the input data during training to avoid local minima.

Rules and ANN can also be applied to the forecasting of the prices of stocks, options, futures, and commodities.

While the purpose of [9] was to minimize forecasting errors, others have been investigating the input data itself to improve the speed and accuracy of the ANN. By feeding the networks with only essential data, or data that would affect the accuracy of the

Table 2.1 Summary Description of Factors [9].

Factor	Description	Low (-1)	High (+1)
1	Hidden layers	One	Two
2	Tr. Fn. In Output Layer	Linear	Sigmoid
3	Tr. Fn. In Hidden Layer	Sigmoid	Sinusoid
4	Learning Algorithm	Standard Backprop	Cumulative Backprop
5	Noise	No Noise	Gaussian Noise
6	Stopping Rule	RMSE	CD
7	Feedback	None	Elman's Network
8	Training Examples	Two Years	Four Years
9	Time of Peak	Winter	Summer
10	Industrial Load%	Low Load %	High Load %

prediction, the training time is greatly reduced. Some low weighted data can have secondary effects as its influence travels trough the hidden layers. Providing the ANN with extraneous information can slow down the training and it can settle on a local minima with weights that are unable to handle variations of larger magnitude in the input data. The inputs of most importance seem to be historical load data and relevant weather data. These may include forecasted weather and load reports.

Forecasting with the Hartley transform

A number of procedures have been developed to re-present the data in such ways as to bring out the patterns normally not seen in the original plots. This data is considered time series data or discrete time series data because it's measured at constant time intervals. Figure 2.4 is a plot of the hourly demand for a particular week. A popular approach to discover trends in time series data is to decompose into a set of sine waves of different frequencies [32]. The decomposition technique most often used is the Fourier Transform. To use the set of data obtained from the Fourier Transform, its magnitudes are squared and plotted versus frequency. An example of this is shown in Figure 2.5. This graph is called a periodogram, line spectrum, or power spectrum. It shows some interesting attributes of the data that might not be so obvious in the plain data plot. It can also confirm trends found by other time series analysis techniques, such as autocorrelation, partial autocorrelation, differences, and ARIMA (AutoRegressive Integrated Moving Average). ANN discovers the trends but usually does not display them other than the direct forecasts.

According to Makridakis [19], the main reasons for using periodograms are to help identify:

- randomness in the data series
- seasonality in a time series
- the predominance of positive or negative autocorrelations

For positive autocorrelation low-frequency amplitudes should dominate, and for negative autocorrelation, high frequencies should dominate [19].

The Fourier Transform takes periodic data and finds the summation of sine waves at

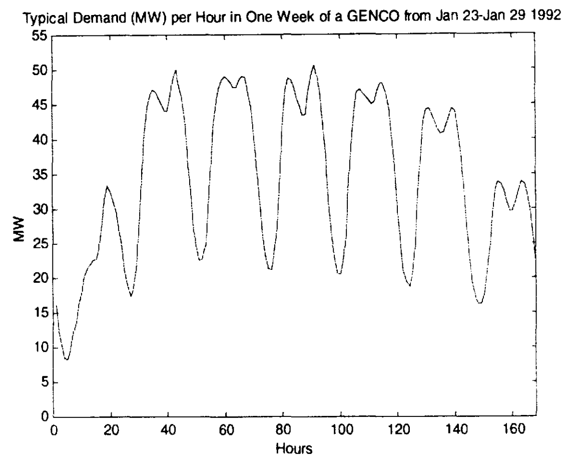

Figure 2.4. Demand of electricity per hour for one week

different frequencies that could be used to reconstruct the original data graph. Note in Figure 2.5 that only the first seven frequencies are needed to construct the original data plot for an acceptable degree of accuracy. The first fourteen is more than enough to match the real times series data. The result of the Fourier Transform comprises both real and imaginary numbers. The complexity of the Fourier transformation may result in excessive computation time and memory usage depending on the size of the problem.

The periodogram, shown in Figure 2.5, confirms that the series is nonstationary because there is a dominance of low-frequency sine waves. A data series is stationary if its statistical properties are independent of the particular time period during which it is observed. According to Makridakis [19], the data from a stationary series fluctuates around a constant mean, independent of time, and the variance of the fluctuation remains essentially constant over time. Usually, the times series data plot itself can convince a forecaster of it's stationarity but it can also be deceiving at times. The data in Figure 2.4 and the periodogram

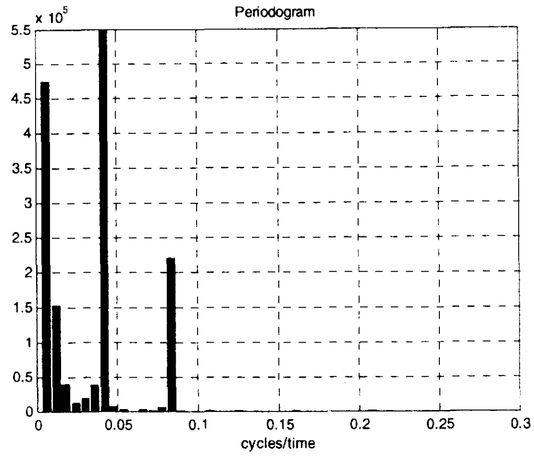

Figure 2.5 Periodogram using FFT.

in Figure 2.5 are clearly not random. The periodogram would have high amplitudes at random frequencies if the data were random. Figure 2.5 also shows that the data is seasonal. Seasonality is a pattern that repeats itself over fixed intervals of time. Of course this data has almost the same pattern every day for a week. The data plot easily exposes this concept.

The periodogram can confirm the same conclusion, but can also provide the period for each season for all data. In Figure 2.5 there are seven amplitudes that dominate the low frequencies. Now, 168 data points divided by 7 gives the period of 24-hour seasonality. This 24-hour seasonality can be seen in Chapter 4 Figure 4.5, where it's explained further. The top plot in Figure 4.5 shows the period exactly at 24, which obviously corresponds to the day period of 24 hours. Again this was known a priori but maybe not if the data was electricity prices, which can fluctuate differently. These are some of the reasons way the Fourier Transform has been used for so long in time series analysis and forecasting.

Hartley Transforms

The Hartley Transform (**HT**) has been around since 1942. Instead of calculating a real and imaginary part, as does the Fourier, it remains in the real numbers set. This is done by the ***cas*** function, developed by Ralph Vinton Lyon Hartley [6]. It is defined as:

$$\boldsymbol{cas\,(vx) \equiv cos(vx) + sin(vx)}$$

This kernel function eliminates the need for complex numbers, although it can be written with them. With the imaginary number dilemma bypassed, computational speeds increase dramatically. Some computers are not equipped for calculations using complex numbers, and these numbers can cause serious problems. The extra memory used to keep track of the excess numbers for the complex calculations can slow down processor speed. Modern high-speed computers can handle most of the calculations but when used in combination with other forecasting programs the processor time really starts to increase.

The Discrete Hartley Transform (DHT) uses the ***cas*** kernel function and is defined as follows:

$$H(v) = N^{-1}\sum_{\tau=0}^{N-1} f(\tau)cas(2\pi\tau v / N)$$

The DHT requires only half the memory space for real data compared to the complex data. For large matrices, this can account for much of the lost space on hard drives.

An alternative way to calculate the Hartley Transform, assuming computation time is not a factor, is the real part of the Fourier Transform minus the imaginary part. This can make use of the FFT and gain some computer speed. A Fast Hartley Transform (FHT) was developed to reduce the time of computation even further. The existence of FHT is one of the reasons the why the Hartley class of transforms is currently being used in a vast number of applications including image processing, circuit analysis, power quality, signal processing, speech processing, fast convolutions, and multidimensional optics applications.

The Hartley Transform is completely reversible. The inverse of the transform is the exact data that was originally transformed. The Hartley Transform does not shift to the same frequency domain as the Fourier. There is a constant of $1/\sqrt{2\pi}$ included in the conversion to keep the transform reversible. This is why the Hartley Transform can be easily used as an alternative decomposition for time series data. A transform that does not require the use of complex numbers is much easier to understand and learn. This is another reason why the Hartley Transform is starting to gain some momentum; it is being taught to beginning engineering students rather than teaching them the Fourier Transform.

Genetic Algorithms

Genetic Algorithms (GA) are also based on principles of biological systems. GA are optimization programs designed to search a solution space with multiple changing solution vectors at the same time. They're basically the concept of the evolution of genetic chromosomes accomplished by Darwin's theory of "survival of the fittest". A GA is constructed in the same way. First a population of individual agents is constructed by encoding them as a bit string or by some other encoding method. This can be referred to as their genes. After this initialization, the GA enters a loop and stays in the loop until a termination condition is met. A termination condition typically occurs when a maximum number of generations or a minimum error range has been attained. In the loop, fitness is calculated using the measure by which the agents are to be judged. In the case of determining if a GA can evolve agents to discover bidding strategies for a double auction for the deregulated electricity industry, the fitness would be driven by the profits attained by the agents. After the fitness is decided, the algorithm for selection of agents from the old population is initiated using a fitness bias. The selected agents will be used to construct the next generation of agents. These "parents" are selected with a random probability with a bias towards the more fit individuals. The methods most commonly used for selections are: Roulette, Rank, and Tournament. [24] will explain more about these selection methods. After the parents are selected, they are paired and are to produce an "offspring" by the recombination of their binary strings. A random crossover point(s) is chosen in the parents' genes. The binary data after the crossover point in the genes are switched between the parents. This creates two children with characteristics of both parents. An example of a single crossover point is shown in Figure 2.6. After the new generation is created, they are mutated. This mutation comes from the biological phenomenon of small changes in the genetic code (DNA) of a creature. The rate of mutation is usually set by the programmer to prevent the GA from becoming trapped in a local optima. The mutation is a change in the bit string at a randomly selected location within the string. In the case of binary bit string, the mutation would change a 1 to a 0 (or visa versa) at that location. This will not have a large effect on the offspring, but would have enough to keep the search space open.

After the mutation of the offspring, the Darwinian step of survival occurs. The creature determined to be less fit will be replaced by the offspring of the agents with a higher "fit" classification. This new generation will now start the next loop in the GA. The basic algorithm can be written as follows [24]:

1. Randomly initialize a population and set the generation counter to zero.

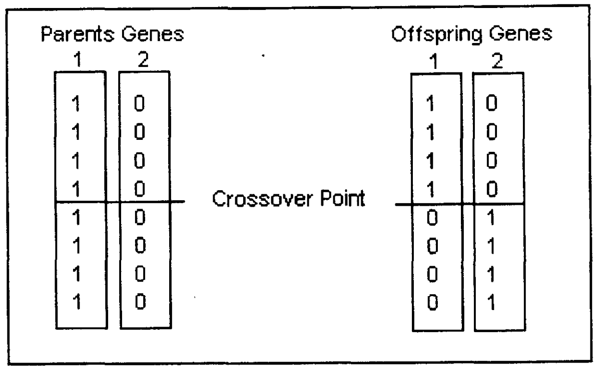

Figure 2.6 Single point crossover.

2. Until done, do the following:

    - Calculate the fitness of each member of the population.
    - Select parents using some fitness bias.
    - Create offspring from the selected parents via crossover.
    - Mutate these new offspring.
    - Replace the lesser-fit member of the population with the newly created offspring.
    - Increment the generation counter and go to the beginning of step 2.

The significance of Genetic Algorithms lies in finding solutions to problems which normal optimization techniques are not able to handle.

The Roth-Erev Algorithm

Roth and Erev [25] [10] have performed many studies to try to understand the learning behaviors of individual people in multi-player strategic games. Through many experiments involving multiple human participants, Roth and Erev developed a three-parameter reinforcement-learning algorithm, from now on referred to as *RE algorithm.*

Roth and Erev used the Law of Effect principle (the tendency of actions that produces a positive affect on a utility function should have their probability of being implemented increased while a negative action's probability is decreased [27]) as a basic starting point for their RE individual learning algorithm. They argue for a supplemental learning provision they refer to as the Power Law of Practice. It states that learning curves tend to be initially steep, after which they flatten out. Most of the research in this area has concentrated on the learning aptitude of one decision maker while playing against nature. Unlike psychologists and their "games against nature", Roth and Erev argue that individual learning in strategic environments with multiple decision makers need more than the Law of Effect and Power of Practice principles to sufficiently account for the observed responsiveness of decision makers to other decision makers in their choice environments.

They argue for two more learning principles to help capture the actual learning behaviors of human subjects. The first is referred to as "Experimentation". It states that choices that were successful in the past are more likely to be used in the future. Also, similar choices will be used more often to produce similar successes. This seems quite intuitive, and makes sense, but was not applied to decision-making agents previously. The second principle, referred to as the "Recency (or Forgetting) effect", states that a more recent experience has a greater affect on current behavior than does an older past experience. This also seems to be a simple concept but only if the recent behavior is beneficial to the agent.

The RE algorithm incorporates each of these four learning principles to some degree. Roth and Erev show that this algorithm is able to track successfully the observed intermediate-term behavior of human subjects over a wide variety of multi-agent repeated games with unique equilibria achievable using stage-game strategies.

To better explain how the learning algorithm works, the RE algorithm is applied to a group of buyers and sellers participating in a double auction. The three parameters characterizing the RE algorithm are a *scaling parameter* s(1), a *recency parameter* r and an *experimentation parameter* e. For simplicity, each buyer and seller is assumed to learn in accordance with an RE algorithm characterized by the same three values for these parameters.

The feasible price offer domain for each buyer and seller is approximated by a discrete grid consisting of K feasible actions (bid or ask prices) k, where K is the same for each trader. At the beginning of the first auction round 1, each trader j assigns an equal *propensity* $q_{jk}(1)$ to each of its feasible actions k, given by $q_{jk}(1)= s(1)X/K$, where X is the average profit that buyers and sellers can achieve in any given auction round.

Additionally, each trader j assigns an equal *choice probability* $p_{jk}(1)$ to each of its feasible actions k, given by $p_{jk}(1) = 1/K$. Each trader j then probabilistically selects a feasible action k′ to submit to the clearinghouse in accordance with its current choice probabilities. On the basis of all received bids and asks, the clearinghouse determines buyer-seller matches. It then communicates these matches back to the traders along with a quantity amount and a midpoint price for each match. Each trader j then implements its assigned trades and records the total profits R(j,k′,1) that it gained from this trading activity.

Now suppose that trader j is at the end of the nth auction round, for arbitrary positive n, and that in the nth auction round trader j has submitted a feasible action k′ to the clearinghouse and achieved total profits R(j,k′,n) from its resulting auction-directed trading activity. Trader j then updates its existing action propensities $q_{jk}(n)$ on the basis of its newly earned profits, as follows. Given any feasible action k, the propensity $q_{jk}(n+1)$ for choosing k in the next auction round n+1 is determined as

$$q_{jk}(n+1) = (1-r)q_{jk}(n) + E(j,k,k',n,K,e)$$

where r denotes the value of the recency parameter, e denotes the value of the experimentation parameter, and $E(\cdot)$ is an update function reflecting the experience gained from past trading activity.

The recency parameter r slowly reduces the importance of past experience, thus implementing the recency effect. The update function $E(\cdot)$ takes the form

$$E(j,k,k',n,K,e) = \begin{cases} R(j,k',n)(1-e), & k = k' \\ R(j,k',n)\dfrac{e}{K-1}, & k \neq k' \end{cases}$$

The selected action k′ is thus reinforced or discouraged on the basis of the profits R(j,k′,n) earned subsequent to this selection, but some propensity to experiment among all other feasible actions k is also retained. Thus, $E(\cdot)$ is an implementation of the experimentation principle.

Given the updated propensities $q_{jk}(n+1)$ for auction round n+1, trader j's updated choice probabilities $p_{jk}(n+1)$ for selecting among its feasible actions k in auction round n+1 take the form

$$p_{jk}(n+1) = \frac{q_{jk}(n+1)}{\sum_{m=1}^{K} q_{jm}(n+1)}$$

In summary, Roth-Erev traders choose the next price based on the profit achieved by past auctions. Recent auctions that produce higher profits have a higher probability of being chosen again. There is a slight glitch when using the RE algorithm and zero profits are obtained but this will be discussed in a later section [21].

New Electricity Market Options

As the electricity industry becomes more and more deregulated or re-regulated, electricity is increasingly thought of as a commodity to be bought and sold on the open market. There are a number of markets on which electricity can be sold. The typical market types are: swap, spot, forwards, futures, and futures options. The spot market is a current and near future market with short-term contracts of up to one month. The forward, futures and option contracts are typically issued from one to eighteen months. A swap contract can be created at essentially any time.

A swap contract is a customized agreement in which two firms agree to trade cash flows at some time(s) in the future. The swapping of interest rates can be used to transform the characteristics of liabilities and assets to conditions mutually beneficial to both parties. This situation arises when a company has a comparative advantage in the floating rates market and another company has a comparative advantage in the fixed rate market. Neither company would prefer to retain the risk of their respective rates. They then agree with each other (either directly or through an intermediary) to swap the interest rates.

The electricity spot market is a market in which sellers and buyers agree (either bilaterally or through an exchange) upon a price and quantity of MWhrs to be delivered sometime in the near future. The physical delivery will need to be cleared through a transmission grid operator (e.g., Regional Transmission Operator (RTO), Independent Contract Administrator (ICA), and/or an Independent System Operator (ISO)) [26]. A forwards contract is a binding agreement in which the seller and buyer agree to an exchange of a specified: amount, physical product, quantity, and future time. In contrast, a futures contract is primarily a financial instrument that allows traders to lock in a price for a commodity in some future month. This helps traders to manage their risk by limiting potential losses or gains. Futures contracts can be considered a kind of insurance. Futures contracts are very detailed on the specifications of the commodity (i.e., quantity, quality, and delivery). Traders of futures contracts usually cancel their positions before the delivery date because they are: not willing to deliver, and/or are not capable of delivering the physical goods. They can do this by purchasing the commodity on the spot market to meet their commitment.

Futures option contracts (see figure 2.7) give the option purchaser the right, but not obligation, to buy or sell a futures contract at a given price (strike price). The price (premium) of an option is based on the amount of future price fluctuation risk the seller acquires by "writing" the option. The seller (writer) of the option takes what is called the "short" position of the option. The buyer (or long position) of the option has the right to buy (call) or the right to sell (put) in the future. More on futures option contracts can be found in [17] [24].

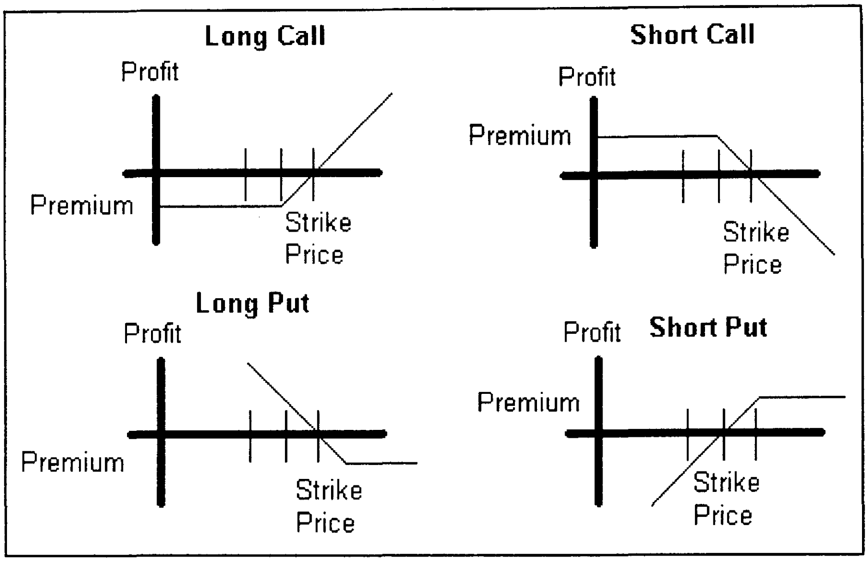

Figure 2.7 Options of options.

Hedging with futures and options

For long term planning a company must be able to meet its goal and keep the company from bankruptcy. When large companies invest millions of dollars into strategic projects, cash flow problems can easily arise if the right decisions are not made about the future. Risky decisions require some insurance for worst-case scenarios. "The term *risk* can be loosely defined as a measure of the lack of predictability of an outcome associated with a particular decision" [24]. Economists use the phrase "utility functions" to describe and order preferences for an individual or a company. A trader's utility should vary directly with actual profit (or expected profit) and indirectly with risk. Separate strategies having the same expected profit can produce diverse exposure to risk.

Futures contracts

Futures contracts allow producers to hedge so that they can limit their loses. Other variables held equal, a GENCO's profit varies with the price of electricity. Predicting the price months in advance so that profit can be known in advance is difficult, especially in today's market of summer price spikes. Simply by considering fuel contracts and using demand forecasts, a profit curve based on the price can be drawn. But not knowing the price creates the potential for large losses. This is where the producers should consider hedging with futures contracts. A hedge with a futures contract is shown in Figure 2.8. A GENCO can

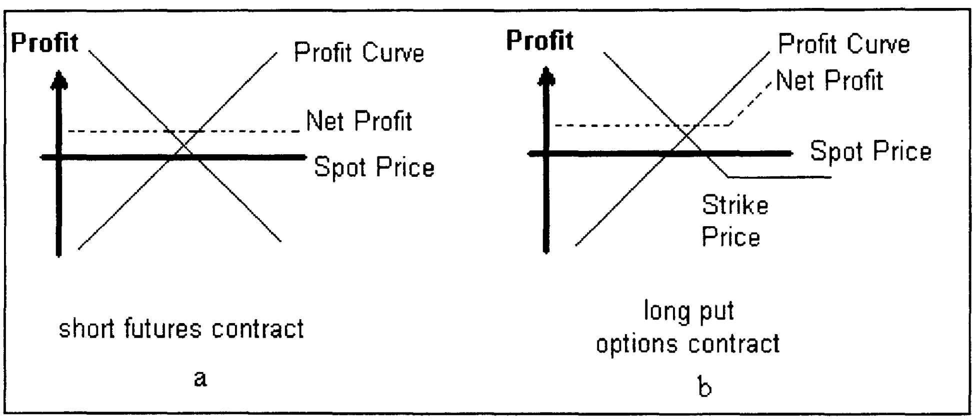

Figure 2.8 Futures (a) and futures option hedging (b).

take a short position (sell electricity not yet produced or next month's electricity) with futures contracts. In the next month, if the spot price is low, they make money on their futures contract and lose money on the electricity sold on the spot market. If the month's spot price is high, then the electricity sold on the spot market yields a profit while the futures contract will produce an offsetting loss. This results in a net profit that is much more predictable due to the hedge.

Futures options contracts

Futures options contracts give the holder the right, but not the obligation, to buy or sell a futures contract. Futures options contracts can be used to reduce risk. When a GENCO wants to maximize profit and reduce its risk in trading, there are alternatives in using futures options, as shown in Figure 2.7. One alternative is that the GENCO pays a premium for an option contract that would give it the right to sell (short) electricity at the strike price. (If the price were higher than the strike price, the GENCO would let the option expire). Figure 2.8 shows how the option contract can be used to hedge profit. If the price is low, the GENCO can exercise the option and assume a futures contract position to offset its losses in the spot market. If the price is high, the GENCO has no obligation to sell at the strike price; the net profit is the profit from the electricity produced by the GENCO and sold on the spot markets less the premium paid for the options contract. The GENCO has limited the amount of money that it can lose, but can still reap the benefits of a high price. Another alternative using futures options would be a short call [24].

Now that electricity futures are sold on the NYMEX (New York Mercantile Exchange) and the CBOT (Chicago Board Of Trade), the ability to hedge in the electricity industry is more available and more complicated. A great deal of analysis and research should go into building strategies that bring together the benefits of these financial and forecasting attributes.

Decision Tree Analysis

Decision tree analysis of some sorts has been studied for some time. It's a decision-making technique to optimize the decision maker's expected utility. "A decision tree is a graphical method of expressing, in chronological order, the alternative actions that are available to the decision maker and the choices determined by chance" [15]. The decision nodes branch out like tree limbs representing different options. These options will have a value and a probability of occurrence assigned. The new options can have more options branched off of them with more probabilities and values. The value of a section of a bough is the summation of probabilities of the values multiplied by the values of all the branches. In figure 2.9, a simple decision tree is shown with both chance and decision nodes. These trees

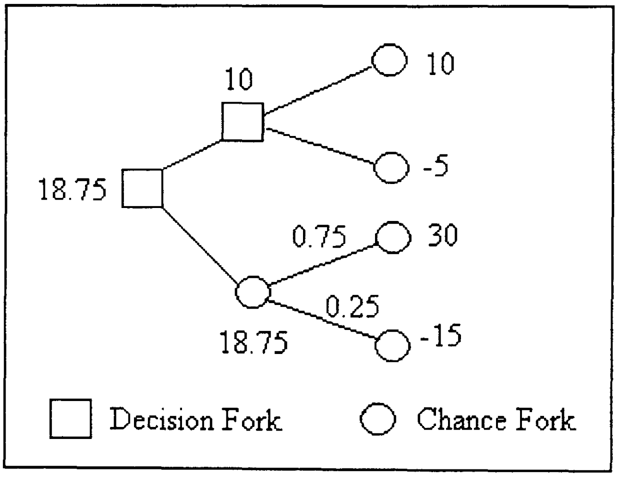

Figure 2.9 Decision Tree with the beginning fork value of 18.75.

can easily show the costs and benefits of certain decisions. Decision trees are constantly applied to project analysis for power systems and financial capital budgeting.

Probability distributions [4]

A traditional method of risk analysis of various inputs (initial conditions and parameters) in modeling uncertainty is Monte Carlo analysis. This method has been successfully applied, but extensive experience has uncovered serious limitations to the technique. One such limitation is if there is a "lack of knowledge sufficient to specify the probability distribution function (PDF) (e.g. normal, lognormal, uniform, etc.) for an uncertain input"[4]. This makes it impossible to draw samples for the Monte Carlo analysis when the distribution function is not known. Another limitation is when there is a "lack of knowledge about the precise nature of the dependency relationships among inputs"[4]. Without the joint probability function, it is impossible to figure out how one input should properly be generated given the other. These limitations have motivated the development of new techniques to overcome them.

A problem with knowing only the mean and variance of a data set is that they can translate into many PDFs. Almost any PDF can be shifted to a specific mean and then stretched or compressed to a specific variance. If all these variations of PDFs are placed on the same graph they would form a mixture that would be difficult to work with. Translating these PDFs into cumulative distribution functions (CDF) on the same graph describes the bounds within which all CDFs in the family lie. "These p-bounded distributions can be used to show possible dependency relationships (e.g. independent, full positive, and negative correlation, and all other dependency relationships) representing the space within each member of that infinitely numerous family."

The Thicket approach uses intervals and associated probability masses. An interval is a range of numbers and the associated probability masses are the probability weight of the interval. These produce a more "stair step" shape to the CDF distribution curves. Convert the p-bounds into easy to handle thickets and then use a combinational calculation on the thickets. Linear programming can be used to find the maximum or minimum of a sum of values given other sums of values that are fixed.

The dependency relationships between events are not necessary to find the CDF space. This technique of p-bounds can be utilized in the decision tree analysis. Finding the correlations between nodes and the probabilities of those events or options happening make the analysis that much more accurate.

All these tools can be applied to the financial decisions of a power company. The applications of forecasting, decision analysis, and competitor modeling can be successfully employed by the full range of employees; from the wholesale electricity traders to the chief financial officers of the company. For the power traders, the competitor modeling of the market auctions can help them develop bidding strategies to maximize the company profits. All employees needing to make decisions can use the decision trees to analyze the bets long-term opportunities. The following chapters will explain how and why the concepts described above can be used to give the deregulated electricity company the skills to survive the modern competitive environment.

CHAPTER 3. METHODS

This chapter explains and describes methods to be used by an electricity market participant to model a competitive market place and other tools to help maximize profits. One method is to simulate agents in a competitive electricity market and see the effects of market power, bidding strategies, and transmission grid constraints. Another method is the utilization of forecasting the load demand in a specific area, which in turn aids in the forecasting of electricity prices in the power market.

GA Computational Electricity Market Overview

This computational electricity market features key attributes of a real-world short-run wholesale electricity market. It includes a few buyers and sellers submitting both price and quantity to a double auction clearinghouse to be matched and approved for profit maximizing contracts. The agents are in control of multi-unit capacities and are modeled with differentiated revenues and cost, unbeknownst to the other agents (hidden information). The buyers and sellers are given the ability to act opportunistically in determining their bids of price and quantity. The agents are able to develop bidding strategies over time that maximizes their profits.

This computational electricity market is attached to a fully connected transmission grid with physical line constraints known as Available Transmission Capacity (ATC). Each trader is assigned a maximum capacity (amount) of electricity that will be bought or sold depending on the agents' functions. A contract between two agents, a buyer and a seller, cannot be more than the ATC of the transmission line connecting them.

Each buyer is assigned the following parameters: capacity in MW; (constant) marginal revenue per MWh purchased and resold in a secondary retail market; and fixed costs. The sellers are assigned the same parameters as the buyers except they have a (constant) marginal cost per MWh generated [21].

This auction model is based on a discriminatory-price double auction. An independent clearinghouse is used to run the auction with buyers and sellers repeatedly trading electricity. Clearly the goal of the buyers and sellers is to maximize profits. Each time the traders submit simultaneous bids of price and quantity is called a round. The buyers' and sellers' marginal cost/revenue functions are linearly derived from actual real world data. The cost/revenue functions along with the discriminatory auction protocols, ensure that the profit maximizing quantity offer is simply the capacity quantity [21]. After the bids and asks are matched and profit is calculated for each trader, the clearinghouse discloses the individual results to their respective trader. The profit maximizing function of the traders together with a modified Roth-Erev individual learning algorithm determines the offers for the next round of trading. A more detailed explanation of the auction round is given in the next section.

One auction round in detail

Each trader selects a bid or ask from their selection set in accordance to the probability assigned to that offer. Also submitted is a quantity of MW the trader is willing to buy or sell at that price. The quantity chosen is always the trader's capacity unless the trader has already been granted a contract using their given capacity. The remaining amount would then be bid in the offer. When the auction clearinghouse has all the offers, it randomly rearranges the order of the traders. This is to reduce the order bias of offers at the same price. This is very possible when small numbers of traders of the same type have similar or identical marginal costs or revenues. The offer ranges are limited to only a certain number of strategies.

A bubble sort is then used to arrange the buyers' bids in descending order and the sellers' asks in ascending order. This is done to match the highest buyer's bid to the lowest seller's ask price. The unit price for the electricity is set at the midpoint of the bid-ask spread. The lowest amount of the: seller's capacity, buyer's capacity, or the ATC between them is used as the contracted amount. For example, if the ATC equaled 7MW, the buyer's capacity was 9 MW, and the seller could sell 20 MW, then the contracted amount would be 7 MW because the transmission line connecting them cannot handle any more power flow. The traders new offer amount is limited to the difference between the trader's original offer and the contracted amount. The next two traders in order are then matched in the same way. Table 3.1 [21] shows an example of the matching outcome between three buyers and sellers with an ATC assumed to be 10MW. The details of how the RE algorithm can be used was previously illustrated in the Literature Review.

A modified Roth-Erev algorithm [21]

The RE algorithm outlined in the Literature Review has two drawbacks: parameter degeneracy; and no probability updating in response to zero profits.

First, the updating of the choice probabilities is slow if *e* is set close to [K-1]/K and ceases entirely if *e* is set equal to [K-1]/K. Consequently, care must be taken in specifying

Table 3.1 Buyer-Seller Matching Illustration.

Sellers	Buyers
\$4 / 20 MWh;	\$9 / 10 MWh
\$5 / 10 MWh;	\$8 / 10 MWh
\$6 / 10 MWh;	\$7 / 10 MWh

Matches: (1-1) for 10 MWh at Unit Price \$7/MWh;
(1-2) for 10 MWh at Unit Price \$6/MWh;
(2-3) for 10 MWh at Unit Price \$6/MWh;
Seller 3 Not Matched.

values for *e* and K.

Second, traders only update the choice probabilities when a non-zero profit is obtained. Zero profit outcomes leave a trader's choice probabilities unchanged because each of the trader's current propensity values are reduced to the same degree. This has the potential to leave a zero profit choice with the same probability as a positive profit producing choice. With no probability updating, a significant loss in market efficiency arises as traders struggle to find the most profitable price offers.

A simple modification of the RE algorithm (first done by Valentin Petrov [21]) addresses both of these problems while still maintaining consistency with the learning principles embodied in the original RE algorithm. Specifically, the update function E(·) in the original RE algorithm was replaced with the following modified update function:

$$ME(j,k,k',n,K,e) = \begin{cases} R(j,k',n)(1-e), & k = k' \\ q_{jk}(n)\dfrac{e}{K-1}, & k \neq k' \end{cases}$$

This modification essentially introduces a differential value for the recency parameter r for selected versus non-selected actions while at the same time omitting the profit term in the updating equation for propensities corresponding to non-selected actions. In particular, the effect is to reduce the magnitude of the recency parameter for non-selected actions from r to r* = (r - e/[K-1]). Clearly degeneracy no longer occurs for e = [K-1]/K.

Note that the shrinkage induced by [1-r] in the propensity value for the selected action is now larger than the shrinkage induced by [1-r*] in the propensity values for non-selected actions. When a zero-profit outcome results from a selected action k', all propensities are reduced, but the propensity corresponding to k' undergoes the most shrinkage. Consequently, in the next auction round the choice probabilities for the non-selected actions will increase relative to the choice probability for k', encouraging the trader to move away from the action that resulted in zero profits.

On the other hand, when the selected action k' results in a positive profit outcome, the positive profit reinforcement in the propensity updating equation for k' will tend to outweigh the larger shrinkage and hence to induce a relative increase in the updated choice probability for this action in the next auction round.

In summary, when the update function E(·) in the RE algorithm is replaced with the modified update function ME(·) (modified RE or MRE algorithm), the zero-profit updating problem is fixed. The choice probabilities corresponding to action choices resulting in zero-profit outcomes tend to decrease while the choice probabilities corresponding to action choices resulting in positive-profit outcomes tend to increase [21].

The calculation of the competitive equilibrium

In order to determine market power and the efficiency of the outcomes, the profits of the buyer and seller in the discriminatory auction have to be compared to the potential profits attained in a competitive equilibrium. "A competitive equilibrium in a market for a positively valued good is a (positive) unit price, P, a total quantity supplied, $Q_S(P)$, and a total quantity demanded, $Q_D(P)$, such that $Q_S(P) = Q_D(P)$"[21]. In other words, the quantity supplied equals the quantity demanded. Note that this supply/demand equation assumes a dependence on the price of the good.

The total supplied or demanded is simply the sum of the all quantities to be sold or bought at price P. Letting $q_i(P)$ denote how much of the good seller i plans to sell at each price P, and $q_j(P)$ denote how much of the good buyer j plans to buy at the same price P, the summation equation are:

$$Q_S(P) = \sum_i q_i(P), \qquad Q_D(P) = \sum_j q_j(P).$$

Both of the supply and demand equations of the individual sellers and buyers are represented as functions of the market price P. This dependence comes from the assumption that these individual supplies and demands are the solutions of competitive profit maximization problems, i.e. profit maximization problems in which the traders are assumed to take the market price P as given [21].

Specifically, for the electricity model at hand, the competitive profit maximization problem for each seller i takes the following form:

$$\underset{q_i}{Max}\ P \cdot q_i - \alpha_i \cdot q_i$$
$$s.t. \quad 0 \le q_i \le CS_i$$

The marginal cost parameter α_i denotes how much it costs seller i to generate each MWh of electricity, and the capacity parameter CS_i denotes an upper bound on the amount that seller i can generate in any one auction round. The solution to this maximization problem is:

$$q_i(P) = \begin{cases} CS_i & \text{if } P > \alpha_i \\ [0, CS_i] & \text{if } P = \alpha_i \\ 0 & \text{if } P < \alpha_i \end{cases}$$

Because this is a competitive market model, no individual seller assumes to be able to affect the market price. If they try to sell at a price above the market price, they will sell nothing. The buyers will just buy from other sellers at or below market price. Of course the sellers can sell all their generation below the market price. The buyers will buy from them before having to buy at the higher market price. Sellers have more incentive to sell at market price because of the higher profit for the same amount of generation.

Likewise, the competitive maximization problem for each buyer j takes the following form:

$$\underset{q_j}{Max}\ r_j q_j - P \cdot q_j$$
$$s.t. \quad 0 \le q_j \le CB_j$$

Here r_j represents the marginal revenue received by buyer j for each MWh of electricity that buyer j resells in a secondary retail electricity market, and CB_j is an upper bound on how much electricity buyer j can resell in any one auction round. The solution to this profit maximization problem is:

$$q_j(P) = \begin{Bmatrix} 0 & \text{if } P > r_j \\ [0, CB_j] & \text{if } P = r_j \\ CB_j & \text{if } P < r_j \end{Bmatrix}$$

The buyers are also assumed to believe that their quantity choices have no effect on the market price P, so this price is taken as an exogenous parameter in their profit maximization problems.

The competitive equilibrium is said to occur at any price P that equates $Q_S(P)$ and $Q_B(P)$. The only computational problem with this definition is the possibility of having an infinite number of equilibria exist. In figure 3.1, an example of this phenomenon is shown. [18] With three buyers and three sellers, each having the capacity of 20 MW, the competitive equilibrium is located at every point on the vertical line segment CE. The competitive equilibrium is the point where the supply and demand curves intersect. To simplify this problem the competitive equilibrium is also taken from the midpoint of all possible competitive prices. For the example in figure 3.1, the CE price would be \$16.50 at 40 MWh.

The agents in the computational electricity model don't actually solve a profit maximization problem. It is used as a benchmark from which the model can be compared to for efficiency and the absence of market power.

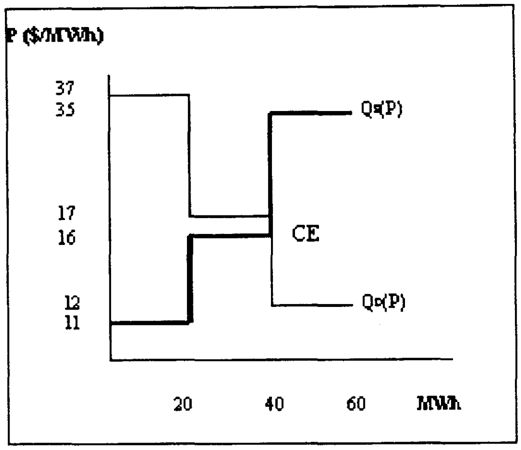

Figure 3.1 Competitive equilibrium for a 3-buyer 3-seller model. Each trader has the same capacity (20 MWh).

Experimental design

The primary purpose of this study is to explore market power and efficiency outcomes for a short-run wholesale electricity market with double auction pricing. Specifically considered was how the relative market power of wholesale buyers and sellers of electricity varies in response to changes in concentration and capacity when prices are determined by means of a discriminatory clearinghouse double auction. Also consider the implications of this discriminatory auction for short-run market efficiency. To achieve these ends, an agent-based computational model of a wholesale electricity market was constructed that can be used as a laboratory for systematic experimentation.

To simplify things, all buyers in this electricity market are assumed to be energy service providers and all sellers are generators, implying that generators do not sell to other generators. Table 3.2 shows the variable definitions and function used to calculate the differences in market power compared to those achieved in a competitive equilibrium.

Table 3.2 Measures of Market Power.

N_B - number of buyers
N_S - number of sellers
Relative Concentration (RCON) of the market - N_S/N_B
CB - maximum amount of electricity (MWh) that each buyer can resell in a retail market
CS - maximum amount of electricity (MWh) that each seller can generate
Relative Capacity (RCAP)

$$RCAP = \frac{N_B \cdot CB}{N_S \cdot CS}$$

PBCE - profits (net earnings) that buyers would obtain in competitive equilibrium
PBA - profits that buyers obtain in the discriminatory auction
Market Power of Buyers (MPB)

$$MPB = \frac{PBA - PBCE}{PBCE}$$

PSCE - profits that sellers would obtain in competitive equilibrium
PSA - profits that sellers obtain in the discriminatory auction
Market Power of Sellers (MPS)

$$MPS = \frac{PSA - PSCE}{PSCE}$$

Efficiency EA of the market - ratio of total auction profits to total profits in competitive equilibrium, measured in percentage terms

$$EA = \frac{PBA + PSA}{PBCE + PSCE} \times 100$$

If the buyers can exert control over the price of electricity in the auction, i.e., if the buyers can exercise market power, then they should be able to raise their profits above their competitive profit level and MPB should be positive. The same is true for the sellers when the MPS is positive.

There are many reasons to be able to acquire market power over the competition or customers. In the electricity market, geography can have influence in the market. With a limited number of transmission lines available to transport the product, the people with control over the ATC have an immense influence on who can buy or sell there. When a single line connects two regions, only so much electricity can flow into or out of the region. When the line has the maximum ATC used up, the price of electricity in that region can go up to the price where it would be cost effective to self-produce electricity. The buyers may be able to push the matching price down long enough for the sellers to choose a strategy of a lower profit than what the sellers could have gained in the competitive equilibrium.

MPB and MPS are measuring the extent to which the profit levels of each buyer and seller in the discriminatory auction differ from the competitive equilibrium. Depending on the aggressiveness of the bidding, an advantage might shift to all buyer or all sellers. If an intra-marginal trader, who would normally match in a competitive equilibrium, decides to engage in opportunistic behavior could be not matched or make a profit. An extra-marginal trader, normally not matched in CE, could get the match by out bidding the opportunistic trader. This should force the traders to bid wisely just to stay in the game. The EA was defined to check for such inefficiencies surfacing in the discriminatory auction.

Tested parameter values

The experimentally tested values for the number of buyers N_B, the number of sellers N_S, the capacity CB of each buyer, and the capacity CS of each seller are given in Table 3.3. The capacities of the buyers and sellers are representative of typical generation and demanded loads. The sums of these capacities are chosen to satisfy the following three test ratios set for relative capacity RCAP: 1:2, 1:1, and 2:1. All buyers are assumed to have

Table 3.3 Tested Parameter Values.

		RCAP	
	1/2	1	2
2	$N_S = 6$ $N_B = 3$ CS = 10 CB = 10	$N_S = 6$ $N_B = 3$ CS = 10 CB = 20	$N_S = 6$ $N_B = 3$ CS = 10 CB = 40
RCON 1	$N_S = 3$ $N_B = 3$ CS = 20 CB = 10	$N_S = 3$ $N_B = 3$ CS = 10 CB = 10	$N_S = 3$ $N_B = 3$ CS = 10 CB = 20
½	$N_S = 3$ $N_B = 6$ CS = 40 CB = 10	$N_S = 3$ $N_B = 6$ CS = 20 CB = 10	$N_S = 3$ $N_B = 6$ CS = 10 CB = 10

identical capacities, and similarly for all sellers. For simplicity, the ATC between each buyer and seller is set at 100 MWh to ensure that the ATC is not a binding constraint on any buyer-seller match under these capacity specifications.

Buyers and sellers are assumed to have linear revenue and cost functions subject to capacity constraints, so that their marginal revenues and marginal costs are constant over their quantity choices up to capacity. The cost functions specified for the sellers are scaled linear approximations of the cost functions of actual generating units.

Table 3.4 shows the specification for marginal revenue (marginal cost) for each buyer (seller) in the experiments reported below. The fixed costs of the buyers and sellers are set to zero for a simpler model. For a seller, this could be representative of a generator already up and running (i.e. synchronized to the transmission grid) and waiting for a match in the auction to connect to the system and deliver electricity.

Table 3.4 Linear Revenue and Cost Curves.

Buyers	Marginal Revenue
1	$37/MWh
2	$17/MWh
3	$12/MWh
4	$37/MWh
5	$17/MWh
6	$12/MWh
Sellers	**Marginal Cost**
1	$35/MWh
2	$16/MWh
3	$11/Mwh
4	$35/MWh
5	$16/MWh
6	$11/MWh

The marginal costs of the sellers are chosen to cover three types of operating costs: expensive, medium, and low-priced. These three types might be representative of an older generation unit, an older unit that has been updated, and a new unit, or of different types of fuel usage. Note from Table 3.4 that, when all six sellers are simulated, two of each type are included to model the competition between similar companies. The buyers' marginal revenues are similar to the marginal costs of the sellers but with enough of a difference to keep a competitive equilibrium profit. This assures the existence of a competitive equilibrium price, which is then used to calculate the benchmark profit levels for market power and efficiency.

Buyers and sellers are not permitted to submit bid or ask prices to the auction that would definitely result in negative profits if accepted. To implement this rationality postulate, the set of feasible bid price offers for each buyer is specified to be the interval [MR-

\$40/MWh, MR], where MR denotes the buyer's true (constant) marginal revenue. Also, the set of feasible ask price offers for each seller is specified to be interval [MC, MC+\$40/MWh], where MC denotes the seller's true (constant) marginal cost. The lower bound MR-\$40/MWh is low enough to encompass all possible ask prices by sellers, and the upper bound MC+\$40/MWh is high enough to encompass all possible bid prices by buyers.

To check the sensitivity of the market power and efficiency outcomes to the specific values set for the parameters characterizing the MRE algorithm (s,r,e), the nine RCAP/RCON configurations in Table 3.3 are tested three times using three different settings for these parameter values.

In the first two tests for Table 3.3, the parameter values for the MRE algorithm are calibrated to facilitate the convergence of the bid and ask prices of the buyers and sellers to unique values by the final auction round in each run. In the first test each run consists of 1000 auction rounds, and in the second test each run consists of 10,000 auction rounds. Calibrations for the parameters were handled in stages. First the number of price offers in a trader's feasible price range was determined by the number of auction rounds per run. For 1000 rounds, 30 possible price offers were randomly selected. In principle a trade could sample each price 33 times. For the 10,000 round case, 100 possible price offers were selected. The second calibration was by direct search of parameters. Values for S(1), r, and e were used when they produced a single peak in the bid and ask histograms by the last round. For the 1000 auction round case were s(1)=1.00, r=0.04, and e=0.97, and the calibrated parameter values found for the 10,000 auction round case were s(1)=1.00, r=0.02, and e=0.99. In the third test for Table 3.3, the scaling parameter s(1), the recency parameter r, and the experimentation parameter "e" for the MRE algorithm are instead set equal to the values obtained in Erev-Roth [10] by a best overall fit of their algorithm to experimental data from twelve distinct types of games run with human subjects. These values are s(1)=9.00, r=0.10, and e=0.20. The RE algorithm with the latter parameter values is referred to below as the *best-fit RE algorithm.*

Effects of Transmission Islanding

The term islanding refers to a situation were the ATC of certain sectors of the network are limited either through already approved contracts or physical constraints on the system. Islanding of a network can be used as a gaming tool in the competitive market. Meaning, when the ATC around a certain section of the transmission grid is unusable because of a variety of constraints, and the demand in the section is greater than the reported supply, the price of electricity in the region will skyrocket. This is also called a price spike. If the ISO/ICA/RTO does not catch this and correct it, it could be a huge money making opportunity for suppliers. One way a power producer could conceivably do this is to make contracts of large amounts of energy over the transmission line around a sector in which the producer is isolated from competitors. Ideally, this would be done by congesting the physical capacity of the lines with low cost contracts. When other suppliers cannot gain access to the sector, the single power producer, or colluding producers, can raise the price of electricity to almost any amount in the short term.

GA market simulations were run to test if agents can learn to take advantage of ATC constraints to make large profits. Running the GA market simulator described above with, and without the Roth-Erev individual learning algorithm was used to test this theory. The inputs were a little different than in the previous simulations. Marginal cost/revenue data was changed to emphasize the effects of the ATC constraints and not the supply demand crossover effects. All the buyers' marginal benefits were set at $20. The sellers' marginal costs were changed to test both a gradual and a more extreme variation to see the difference in the islands. The sellers' marginal costs are listed in table 3.5.

First a full "equal access" grid was simulated with the same test data to be used on the limited access grids. This was to obtain control results to compare later. Then the transmission grid for the buyers and sellers were gradually split into two separate islands to

Table 3.5 Seller's marginal costs.

Seller's Marginal Costs in Order	
15	15
12	15
10	15
10	5
10	5
5	5

see if different matching prices would evolve from the different marginal revenue/cost data. This was implemented with limited access for the top right and bottom left corners (first and third quadrants) of the grid, decreasing from 7 to 3 to 1 as in Table 3.6. This semi-limited arrangement could be used to show the effects of some contracts already limiting access to a sector or the physical lines were not built with enough capacity to supply the region.

The third simulation was to see if the system can evolve the agents with two totally isolated islands as in Table 3.7. The third test would represent the situation were a producer or group of producers have isolated a sector with contracts or "planned outages". The

Table 3.6 ATC of Semi-Separation of Grid.

10	10	10	7	3	1
10	10	10	7	3	3
10	10	10	7	7	7
7	7	7	10	10	10
3	3	7	10	10	10
1	3	7	10	10	10

separate islands should develop their own price, independent of the other island, especially in the case where the sellers' marginal costs are 15 and 5.

The GA simulations were set for 50 runs of 100 auction rounds. When the Roth-Erev simulations were run, 100 runs of 1,000 auction rounds were executed. The parameters used were the *best-fit RE* type as described above. The average and standard deviation were then taken to get a feel of where the matched bids were settling. The average discriminatory price was calculated for all the cases. In the separate islands case, an average discriminatory price could be calculated for each island. With the semi-separated case, this could not be calculated because the islands were not well defined.

Table 3.7 ATC Islanding of Grid.

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

Artificial Neural Networks Short Term Load Forecasting

To see the effectiveness of a simple STL forecaster, one was programmed using Matlab. A simple three-layered feedforward backpropagation was programmed with the only input to the network being hourly load amounts. This simple ANN was set up to read in three consecutive week's worth of load data and forecast the fourth. The week of data chosen was during the early summer with a general load pattern (i.e., no holidays or really hot days). On a hot day, the load from the use of air conditioners is dramatically increased. On a holiday, the load pattern can be much different compared to regular weekdays or weekends. Research has shown that when a simple network is shown limited data with large single variations the forecast will be inaccurate. While a more sophisticated ANN with rather large data sets would benefit from some noise variations to be able to handle the uncommonly large or small load demands. After the week forecasting simulation, the network was told to forecast for just the next three days. The contrast of short and longer forecasts will show accumulation of error with an extended prediction.

In the next chapter, the results of the above techniques will be revealed. These techniques can be used in combination to provide the necessary information to assess the most prudent financial decisions possible. The STLF can be used in conjunction with the decision analysis to decide on the building of future generation expansion. The STLF may be combined with the computational electricity market to make better predictions on the future price of electricity. The combinations of what decision and what analytical tools to use to solve them really start to expand at this point. The next chapter will give a better idea on what these tools can begin to solve.

CHAPTER 4. EXPERIMENTAL RESULTS

GA Computational Electricity Market

The results of the auction runs are shown in a series of tables. Auction Table 4.1, Table 4.2, and Table 4.3 [21] report cumulative and individual market power outcomes and efficiency outcomes for the following three learning specifications, respectively: (a) the calibrated MRE algorithm with each run consisting of 1,000 auction rounds; (b) the calibrated RE algorithm with each run consisting of 10,000 auction rounds; and (c) the best-fit RE algorithm with each run consisting of 1,000 auction rounds. Each cell in each table corresponds to a unique RCAP/RCON configuration, in accordance with Table 3.3. All cells were the results of the running the auction 100 times. For each run, the profit levels attained in the final auction round by buyers and sellers as a whole, as well as by individual buyers and sellers, were calculated and compared against competitive equilibriua profit levels to obtain aggregate and individual MPB and MPS market power indices. Additionally, for each run, a value for the market efficiency measure EA was calculated and recorded.

The means and standard deviations of the cumulative and individual MPB and MPS market power indices were then calculated across all 100 runs for each table cell. The mean market power result with a positive or negative sign is marked with an asterisk when it is substantially different from zero, in the sense that the indicated sign does not change when the outcome is either increased or decreased by one standard deviation. Finally, the mean and standard deviation for the market efficiency measure EA calculated across all 100 runs are given at the bottom of each table cell. Figure 4.5 shows the ask price of Seller 3 from the last auction round of all 100 runs. There is a plot for each of the three sets of parameters. Table 4.4 shows the analytically derived structural market power results. Structural market power

Table 4.1 Experimental market power and efficiency outcomes using the calibrated MRE algorithm with 1000 auction rounds and parameter values s(1) = 1.00, r = 0.04, and e = 0.97. ZP indicates zero profits were earned both in the auction and in competitive equilibrium.

Relative Concentration		Relative Capacity: 1/2 MP	1/2 StdDev	1 MP	1 StdDev	2 MP	2 StdDev
2	All Buyers:	-0.27	(0.18)	-0.23 *	(0.17)	-0.06	(0.28)
	All Sellers:	0.46	(0.88)	0.29	(0.48)	-0.24	(0.33)
	Buyer[1]:	-0.24	(0.26)	-0.21*	(0.19)	-0.06	(0.28)
	Buyer[2]:	-0.68*	(0.50)	-0.87	(0.96)	ZP	(0.00)
	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[2]:	ZP	(0.00)	1.75	(5.46)	-0.24	(0.46)
	Seller[3]:	0.37	(1.97)	0.17	(0.85)	-0.24	(0.37)
	Seller[4]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[5]:	ZP	(0.00)	1.39	(4.71)	-0.22	(0.44)
	Seller[6]:	0.54	(1.32)	0.19	(0.80)	-0.25	(0.37)
	Efficiency:	100.00	(7.70)	96.30	(10.72)	77.60	(14.75)
1	All Buyers:	-0.37*	(0.20)	-0.26*	(0.17)	-0.13	(0.37)
	All Sellers:	0.55	(0.67)	0.44	(0.56)	-0.27	(0.37)
	Buyer[1]:	-0.33*	(0.20)	-0.24*	(0.18)	-0.13	(0.37)
	Buyer[2]:	-0.73*	(0.50)	-1.00	(0.00)	ZP	(0.00)
	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[2]:	ZP	(0.00)	2.37	(6.49)	-0.29	(0.51)
	Seller[3]:	0.40	(0.86)	0.27	(0.90)	-0.25	(0.37)
	Efficiency:	86.88	(17.91)	96.48	(4.63)	90.98	(23.55)
1/2	All Buyers:	-0.33*	(0.16)	-0.25*	(0.16)	0.01	(0.33)
	All Sellers:	0.55*	(0.50)	0.44	(0.44)	-0.21	(0.25)
	Buyer[1]:	-0.29*	(0.19)	-0.21*	(0.17)	0.01	(0.43)
	Buyer[2]:	-0.68*	(0.52)	-1.00	(0.00)	ZP	(0.00)
	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Buyer[4]:	-0.29*	(0.17)	-0.25*	(0.24)	-0.03	(0.44)
	Buyer[5]:	-0.68*	(0.49)	-0.98*	(0.20)	ZP	(0.00)
	Buyer[6]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[2]:	ZP	(0.00)	0.77	(4.60)	-0.25	(0.37)
	Seller[3]:	0.37	(0.76)	0.41	(0.72)	-0.18	(0.31)
	Efficiency:	85.53	(17.85)	96.39	(4.04)	96.55	(12.70)

Table 4.2 Experimental market power and efficiency outcomes using the calibrated MRE algorithm with 10,000 auction rounds and parameter values s(1) = 1.00, r = 0.02, and e = 0.99. ZP indicates that zero profits were earned both in the auction and in competitive equilibrium.

Relative Concentration		Relative Capacity 1/2: MP	StdDev	1: MP	StdDev	2: MP	StdDev
2	All Buyers:	-0.04	(0.07)	-0.07	(0.26)	-0.07	(0.24)
	All Sellers:	0.19	(0.32)	0.21*	(0.19)	-0.06	(0.19)
	Buyer[1]:	-0.04	(0.06)	-0.07*	(0.05)	-0.07	(0.24)
	Buyer[2]:	-0.04	(0.33)	-0.30	(0.47)	ZP	(0.00)
	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[2]:	ZP	(0.00)	-0.15	(0.79)	-0.06	(0.24)
	Seller[3]:	0.23	(0.44)	0.26*	(0.22)	-0.06	(0.17)
	Seller[4]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[5]:	ZP	(0.00)	-0.30	(0.63)	-0.06	(0.25)
	Seller[6]:	0.14	(0.36)	0.24*	(0.21)	-0.06	(0.17)
	Efficiency:	100.00	(0.00)	99.49	(0.91)	100.00	(0.00)
1	All Buyers:	-0.16*	(0.09)	-0.08*	(0.07)	0.06	(0.24)
	All Sellers:	0.60*	(0.38)	0.22	(0.28)	-0.05	(0.19)
	Buyer[1]:	-0.14*	(0.07)	-0.08*	(0.07)	0.06	(0.24)
	Buyer[2]:	-0.30	(0.38)	-0.30	(0.58)	ZP	(0.00)
	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[2]:	ZP	(0.00)	-0.05	(1.15)	-0.05	(0.24)
	Seller[3]:	0.60*	(0.38)	0.25	(0.32)	-0.04	(0.16)
	Efficiency:	94.13	(8.66)	99.66	(1.07)	100.00	(0.00)
1/2	All Buyers:	-0.14*	(0.07)	-0.06*	(0.05)	0.10	(0.20)
	All Sellers:	0.59*	(0.36)	0.20*	(0.19)	-0.08	(0.16)
	Buyer[1]:	-0.14*	(0.06)	-0.06	(0.06)	0.10	(0.20)
	Buyer[2]:	-0.24	(0.36)	-0.31	(0.60)	ZP	(0.00)
	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Buyer[4]:	-0.12*	(0.06)	-0.06	(0.06)	0.10	(0.20)
	Buyer[5]:	-0.23	(0.34)	-0.27	(0.64)	ZP	(0.00)
	Buyer[6]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
	Seller[2]:	ZP	(0.00)	ZP	(0.00)	-0.10	(0.20)
	Seller[3]:	0.59*	(0.36)	0.20*	(0.19)	-0.07	(0.14)
	Efficiency:	95.22	(8.05)	99.56	(0.79)	100.00	(0.00)

Table 4.3 Experimental market power and efficiency outcomes using the best-fit MRE algorithm with 1000 auction rounds and parameter values s(1) = 9.00, r = 0.10, and e = 0.20. ZP indicates that zero profits were earned both in the auction and in competitive equilibrium.

Relative Concentration		Relative Capacity 1/2 MP	StdDev	Relative Capacity 1 MP	StdDev	Relative Capacity 2 MP	StdDev
2	All Buyers:	-0.13*	(0.09)	-0.15*	(0.09)	0.10	(0.30)
2	All Sellers:	0.55*	(0.38)	0.38*	(0.33)	-0.10	(0.25)
2	Buyer[1]:	-0.12*	(0.08)	-0.13*	(0.10)	0.10	(0.30)
2	Buyer[2]:	-0.20	(0.40)	-0.75*	(0.33)	ZP	(0.00)
2	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
2	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
2	Seller[2]:	ZP	(0.00)	-0.50	(1.34)	-0.12	(0.34)
2	Seller[3]:	0.54	(0.63)	0.45*	(0.40)	-0.10	(0.22)
2	Seller[4]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
2	Seller[5]:	ZP	(0.00)	-0.42	(1.67)	-0.08	(0.36)
2	Seller[6]:	0.55	(0.60)	0.46*	(0.41)	-0.09	(0.24)
2	Efficiency:	100.00	(1.88)	96.30	(4.51)	100.00	(5.86)
1	All Buyers:	-0.22*	(0.12)	-0.13*	(0.10)	0.13	(0.33)
1	All Sellers:	0.80*	(0.53)	0.28	(0.35)	-0.10	(0.26)
1	Buyer[1]:	-0.21*	(0.11)	-0.11*	(0.10)	0.13	(0.33)
1	Buyer[2]:	-0. 31	(0.44)	-0.80*	(0.40)	ZP	(0.00)
1	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
1	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
1	Seller[2]:	ZP	(0.00)	-0.37	(1.89)	-0.10	(0.34)
1	Seller[3]:	0.76*	(0.63)	0.34	(0.45)	-0.11	(0.24)
1	Efficiency:	92.13	(9.30)	94.59	(6.69)	100.00	(0.00)
1/2	All Buyers:	-0.21*	(0.12)	-0.14*	(0.08)	0.09	(0.24)
1/2	All Sellers:	0.67*	(0.46)	0.30	(0.31)	-0.07	(0.19)
1/2	Buyer[1]:	-0.18*	(0.12)	-0.14*	(0.10)	0.09	(0.27)
1/2	Buyer[2]:	-0.37	(0.47)	-0.77*	(0.44)	ZP	(0.00)
1/2	Buyer[3]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
1/2	Buyer[4]:	-0.20*	(0.11)	-0.11	(0.11)	0.10	(0.25)
1/2	Buyer[5]:	-0.38	(0.47)	-0.73*	(0.46)	ZP	(0.00)
1/2	Buyer[6]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
1/2	Seller[1]:	ZP	(0.00)	ZP	(0.00)	ZP	(0.00)
1/2	Seller[2]:	ZP	(0.00)	0.14	(2.69)	-0.08	(0.27)
1/2	Seller[3]:	0.63*	(0.55)	0.32	(0.48)	-0.07	(0.17)
1/2	Efficiency:	91.84	(9.00)	94.24	(7.26)	100.00	(0.00)

Table 4.4 Analytically derived structural market power outcomes.

	1/2	**Relative Capacity** **1**	**2**
2	All Buyers: -0.14 All Sellers: 0.56 Buyer[1]: -0.43 Seller[3]: 3. 33 All Others: 0.00	All Buyers: -0.12 All Sellers: 0.45 Buyer[1]: -0.37 Seller[3]: 1.36 Seller[6]: 1.36 All Others: 0.00	All Buyers: 0.04 All Sellers: -0.05 Buyer[1]: 0.12 Seller[3]: -0.16 Seller[6]: -0.16 All Others: 0.00
Relative Concentration **1**	All Buyers: -0.14 All Sellers: 0.56 Buyer[1]: -0.43 Seller[3]: 1.67 All Others: 0.00	All Buyers: -0.12 All Sellers: 0.45 Buyer[1]: -0.37 Seller[3]: 1.36 All Others: 0.00	All Buyers: 0.04 All Sellers: -0.05 Buyer[1]: 0.12 Seller[3]: -0.16 All Others: 0.00
1/2	All Buyers: -0.14 All Sellers: 0.56 Buyer[1]: -0.43 Buyer[4]: -0.43 Seller[3]: 1.67 All Others: 0.00	All Buyers: -0.12 All Sellers: 0.45 Buyer[1]: -0.37 Buyer[4]: -0.37 Seller[3]: 1.36 All Others: 0.00	All Buyers: 0.04 All Sellers: -0.05 Buyer[1]: 0.24 Seller[3]: -0.16 All Others: 0.00

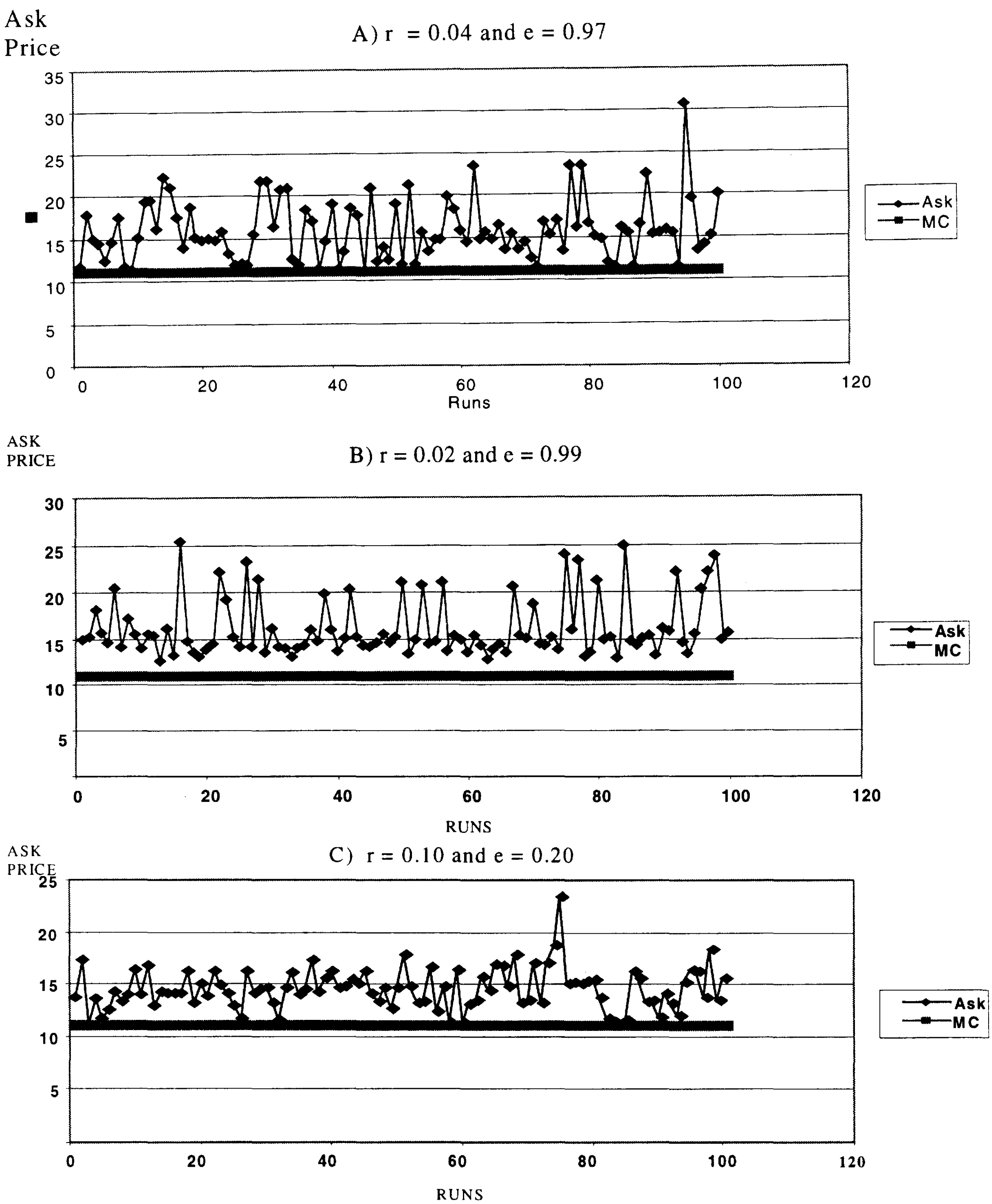

Figure 4.5. Plot of the ask price for Seller 3 in cell (3,1) in the final generation across all 100 runs under three different RE algorithm specifications: A) Table IV -- calibrated RE algorithm with 1000 auction rounds per run; B) Table V -- calibrated RE algorithm with 10,000 auction rounds per run; and C) Table VI -- best-fit RE algorithm with 1000 auction rounds per run.

will be explained in the conclusion.

Simple ANN STLF

Programmed in MATLAB, a simple 3-layer feedforward backpropagation ANN was tested for a forecast of three days with a month's worth of data. With these simple inputs and no weather data. The ANN was able to forecast with a .14 error. As seen in figures 4.1 and 4.2, an ANN's forecast (without the weather data usually used) is similar to the accuracy found in recent ANN STLF publications. Figure 4.1 shows the forecast for a week using the proceeding 3 weeks as a pattern. Figure 4.2 shows the prediction of the next three days using

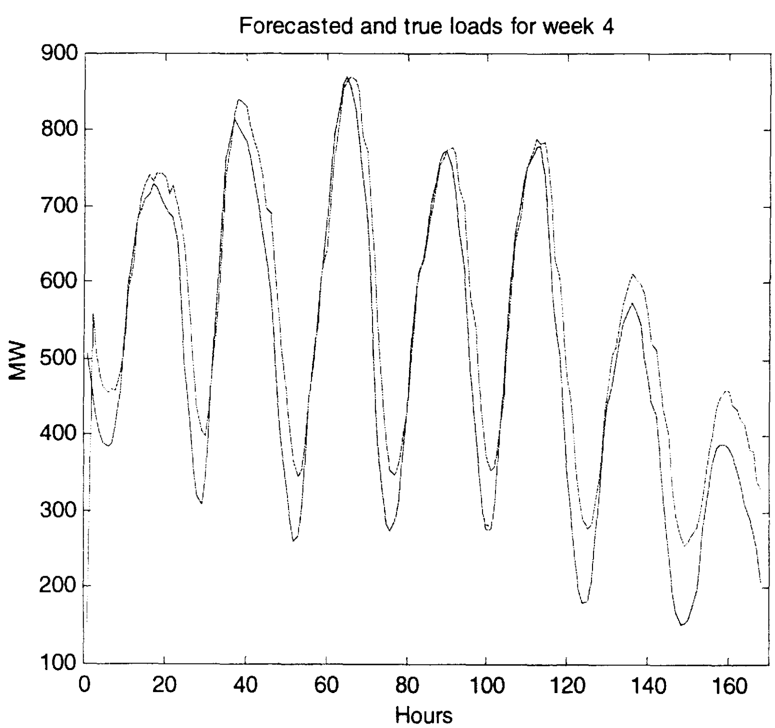

Figure 4.1 Simple ANN STLF.

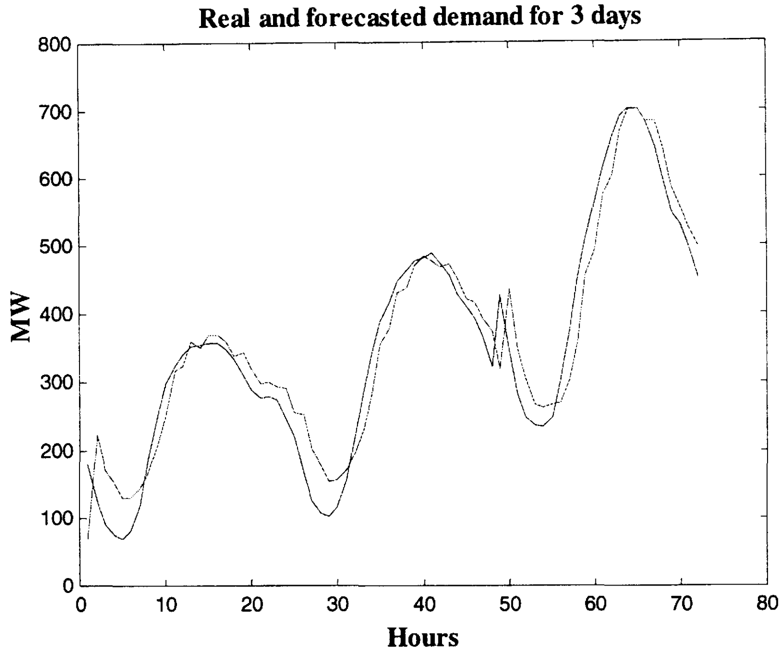

Figure 4.2 Output of a simple ANN for a 3 day period.

the data for those same three days of the last three weeks.

Comparison of FFT and FHT

As seen in Figure 4.3, the HT will produce a line spectrum very similar to the line spectrum produced by the FFT. The amplitude will not be the same but the general pattern is similar. Hence, the same trend information used for forecasting and modeling the systems can be obtained using the FHT. A direct comparison is shown in Figure 4.4. As stated earlier, the amplitudes are not the same magnitude so the graphs have been scaled to show the details

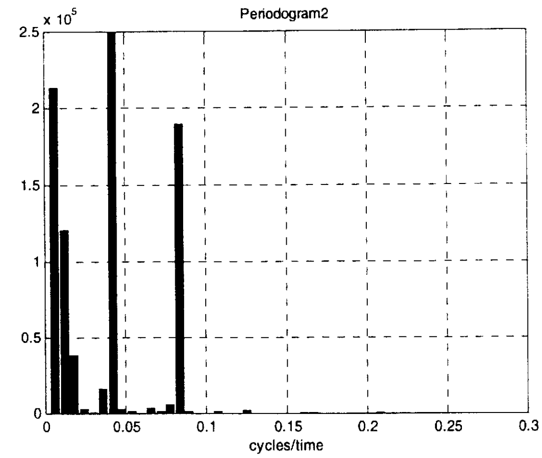

Figure 4.3 Periodogram using Hartley Transforms.

of each transform characteristics in their respective periodograms. The bars on the graphs match up perfectly. The seasonality is exactly the same between the two transforms. Each has a season set of seven (the first set of amplitudes higher than their neighbors). The season for the data is 24 hours, as calculated earlier. The other seasonality evaluation is shown in Figure 4.5. It shows a period exactly at the 24 mark in both the FHT version and in the FFT version. The other peak represents a smaller correlation to the 12-hour period. This can also be seen in Figure 4.4. After the Initial seasonal set, the next peak is located at the 14th amplitude. The season period calculates to 12 hours, the same shown in Figure 4.5.

There are many advantages to use the DHT over the DFT. The DHT performs fewer operations that may lead to less truncation and rounding errors from computer finite word length [16]. This can stem from different math co-processors and the version of the CPU. Obviously, when a math error occurs at the beginning of the calculations it will just become compounded as the calculations continue. A problem such as this can throw off any sort of accurate short-term forecasting. Long-term forecasting would develop trends that would not

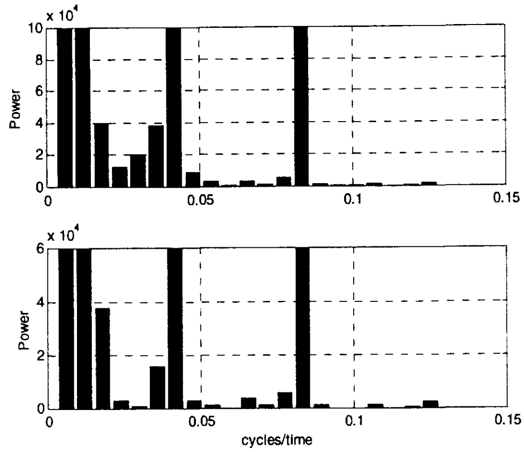

Figure 4.4 Comparison of FFT (top) and HT(bottom) periodograms.

exist. In a competitive environment such mistakes can throw a company right into bankruptcy.

The complement to the reduced-error argument is the complexity of the DFT as compared to the DHT. Not only is there a potential for errors because of rounding and truncation, there is a definite concern for the complexity of the DFT itself. Many people have a hard time learning the concept and algorithms associated with the Fourier transform. The switching from time domain to frequency domain develops problems for some engineers. Some people have a hard time understanding the real value with using imaginary numbers for practical purposes. The FHT is its own inverse which reduces the complication of reversing the transform considerably, especially compared to the Fourier's extra algorithms. Forecasting should be easy enough for all employees to understand and use, not just the people with enough background and practice with Fourier transforms. In the competitive market, electricity price forecasting need to be explained to the company. Executives will be inclined to go with the formula that does not include "imaginary numbers". For some applications such as circuit theory and power systems analysis there is an advantage of knowing the phase and magnitudes separately. The Hartley Transform has been developed to the point were it to can be used for such applications with the added advantage of the much faster FHT. These developments were due mostly because of the FHT. Its speed and reliability has given reason to the pursuit of other applications.

Another real advantage of the FHT is the speed of calculation compared to the DFT. The speed ratio between the DFT and the FFT convolutions is ρ/N, where N is the number of data points to be transformed and $N=2^{\rho}$. For example, if $N = 2^{10}$, the FFT would require less than 1% of the normal computing time [16]. "Timing studies have shown that for N greater then about 28, the FFT method is at least an order of magnitude faster" than a lagged products approach of calculating the same convolution [16]. Now consider that the FHT is quicker than the FFT. It could be as much as twice as fast. The time saved in computation alone is a tremendous advantage over the competition.

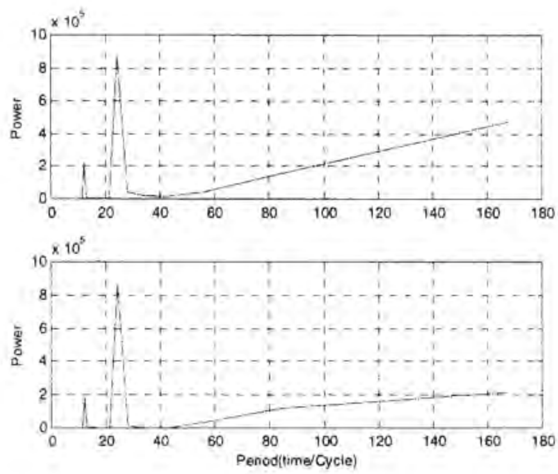

Figure 4.5. Season of the FFT periodogram (top) and HT (bottom).

Transmission system with constraints

The next sets of figures are the results from testing how the bidding strategies change as the ATC are constrained to the point where two separate islands are formed. Figures 4.6 and 4.7 show the bidding strategy of sellers 3 and 4 with full ATC and marginal costs following Table 3.5. Figure 4.6 is the result of sellers 3 with a MC of 15 and seller 4 with a MC of 5. Figure 4.7 is the product of 10 for both sellers MC. Figures 4.8 and 4.9 show a semi-constrained ATC as pertaining to Table 3.6. Figures 4.10 and 4.11 show the fully constrained (two separate islands) network strategies for the sellers 3 and 4 as they correspond to Table 3.7. To better show the consequences of the fully constrained islands, Figures 4.12 – 4.15 show the strategies of the individual islands over the 100 runs. Island one refers to the upper left hand corner island as seen in Table 3.7. Island two refers to the lower right hand corner also seen in Table 3.7. Table 4.6 contains the market power indices for the constrained electricity networks.

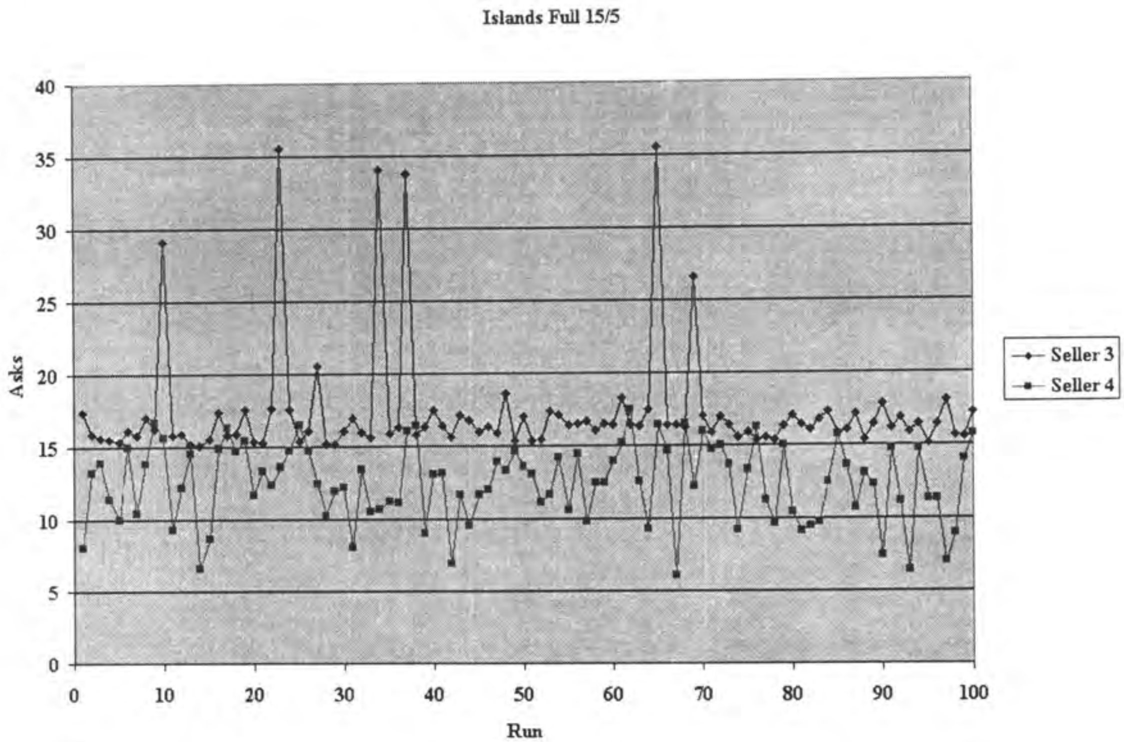

Figure 4.6 100th Ask for Sellers 3 and 4 with full ATC (MC 15/5).

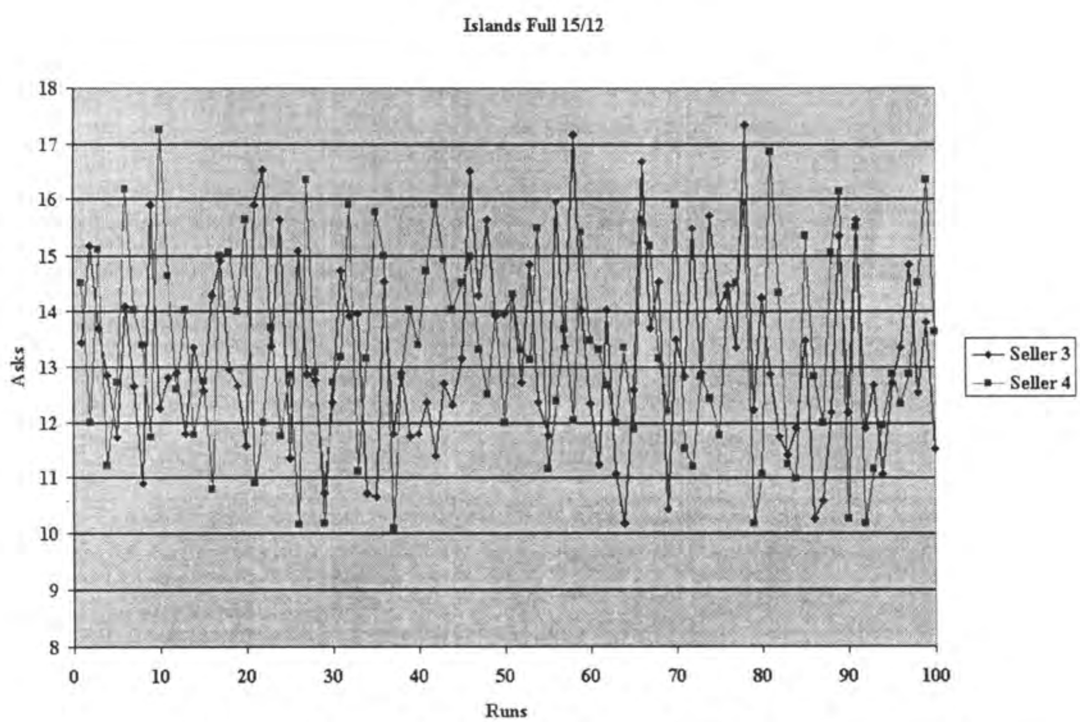

Figure 4.7 100th Ask for Sellers 3 and 4 with full ATC (MC 15/12).

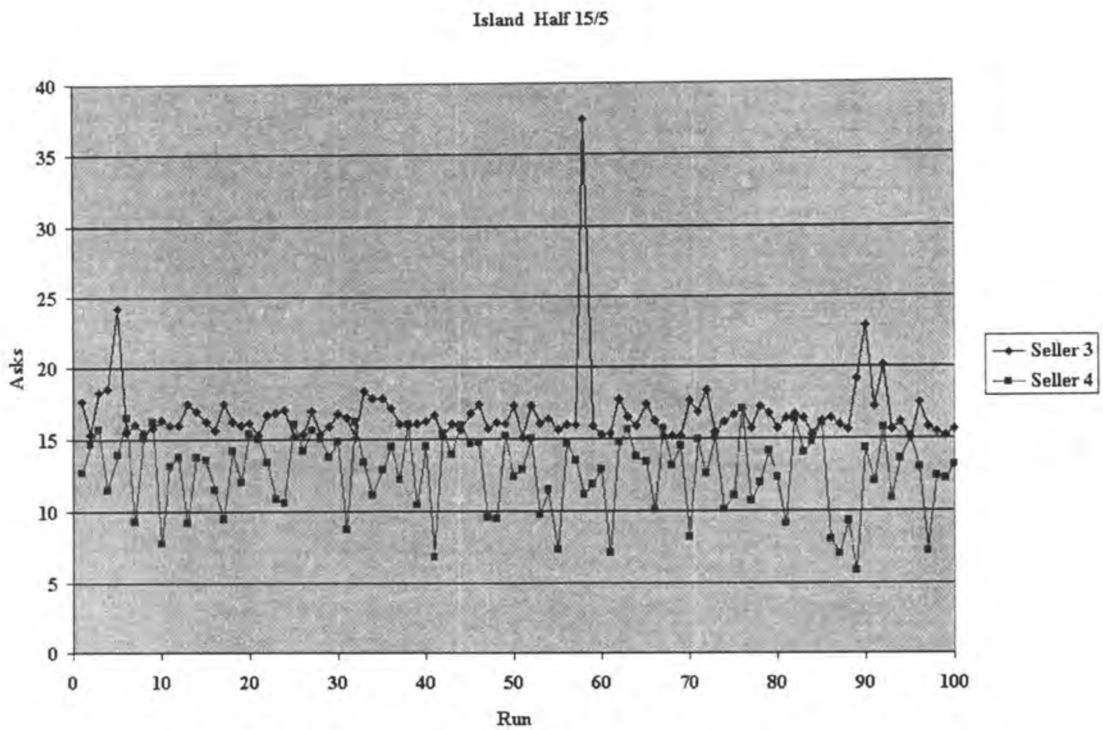

Figure 4.8 100th Ask for Sellers 3 and 4 with constrained ATC (MC 15/5).

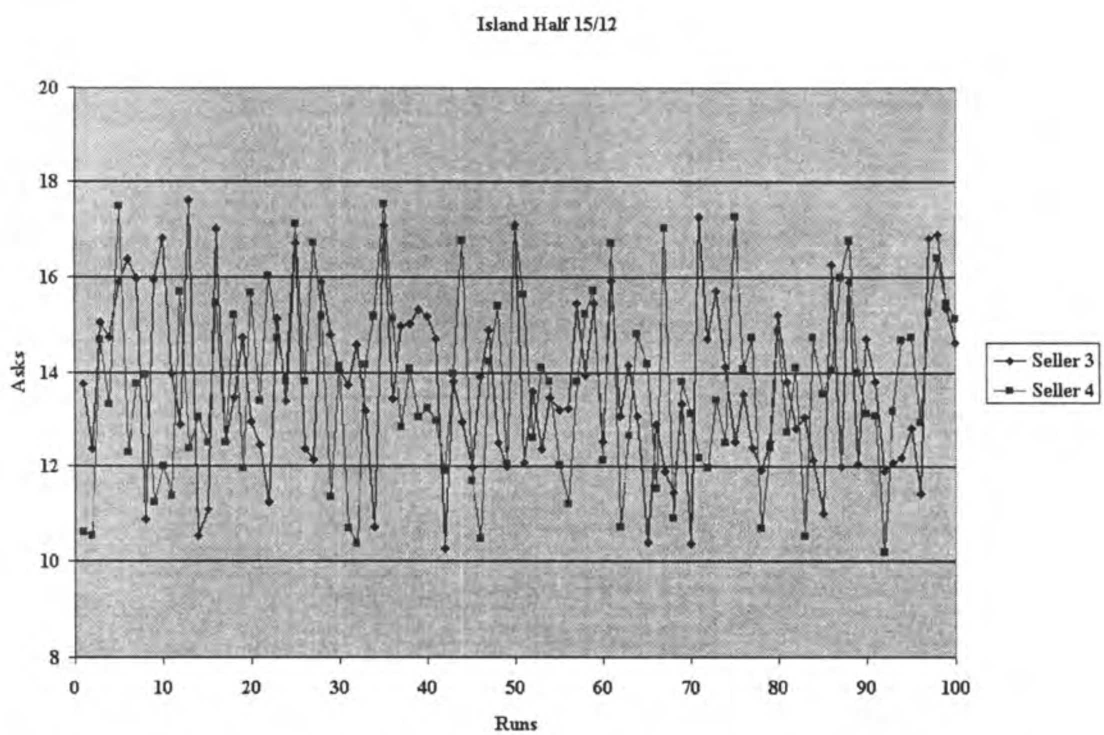

Figure 4.9 100th Ask for Sellers 3 and 4 with constrained ATC (MC 15/12).

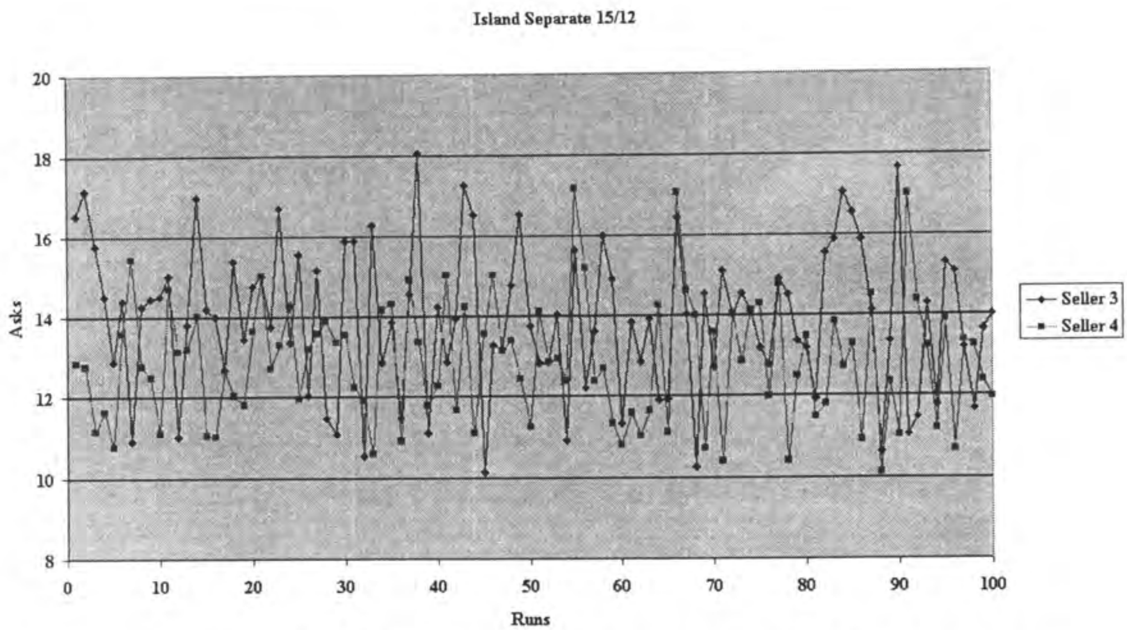

Figure 4.10 100th Ask for Sellers 3 and 4 with separate ATC (MC 15/12).

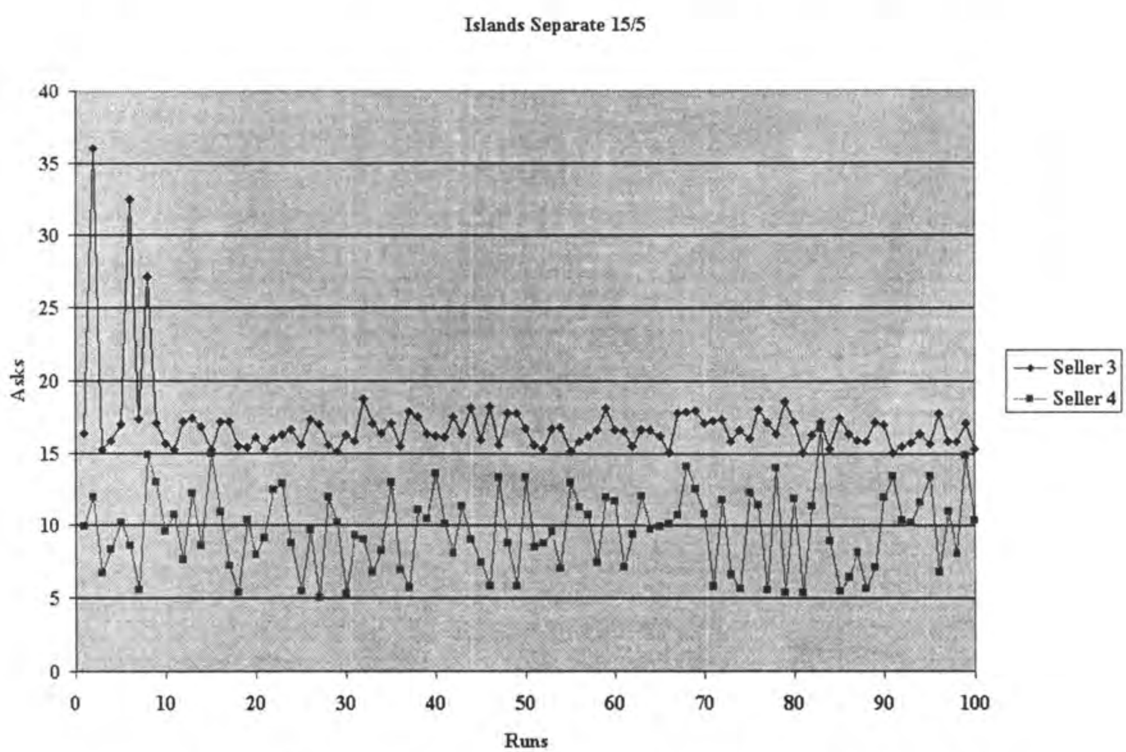

Figure 4.11 100th Ask for Sellers 3 and 4 with separate ATC (MC 15/5).

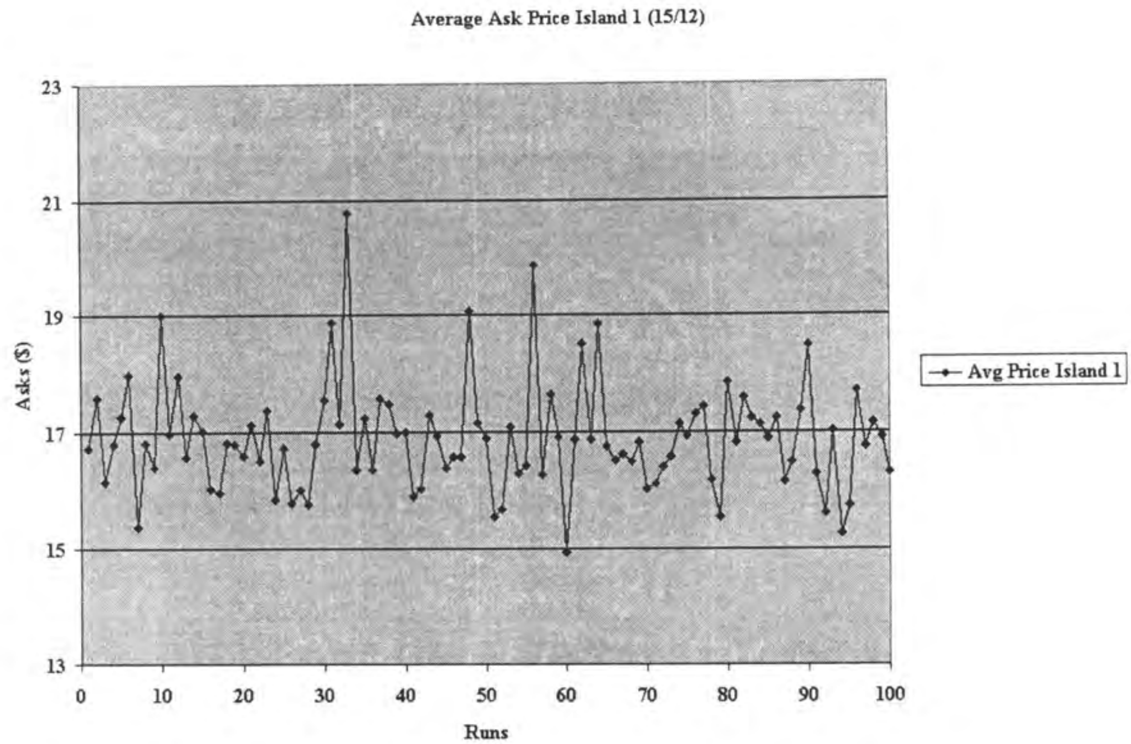

Figure 4.12 100th average Ask for Island 1 with separate ATC (MC 15/12).

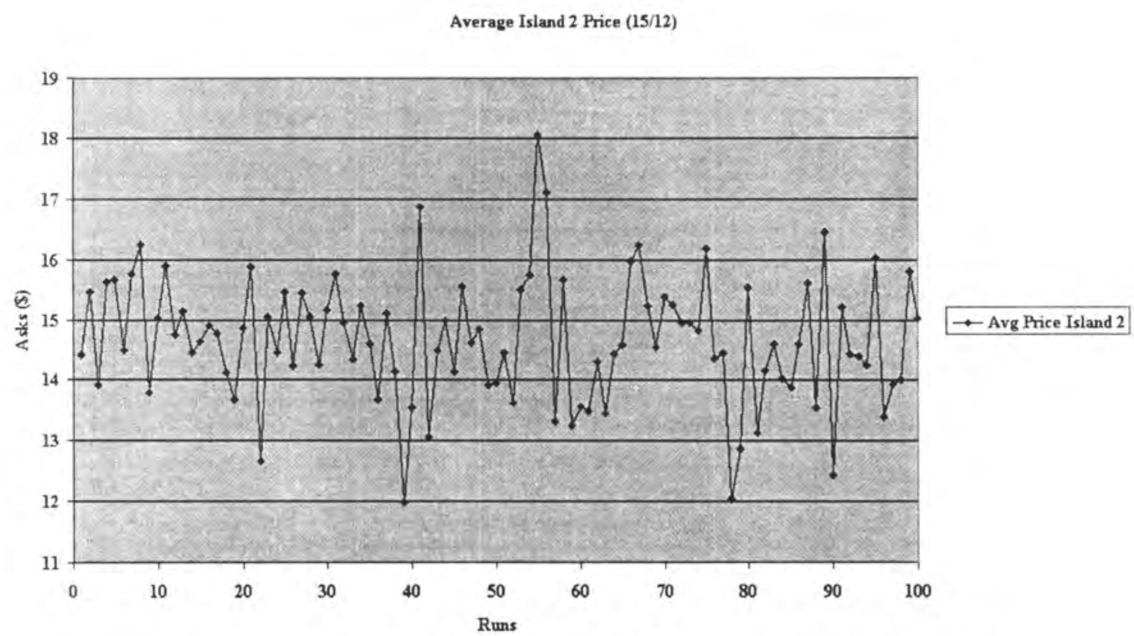

Figure 4.13 100th average Ask for Island 2 with separate ATC (MC 15/12).

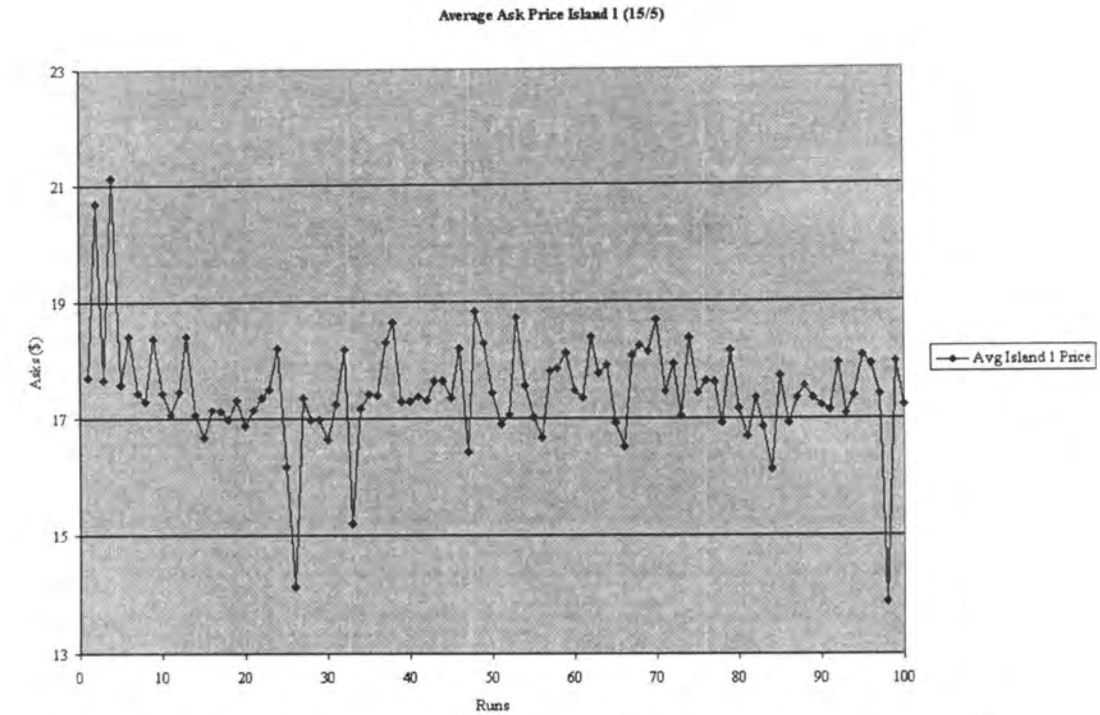

Figure 4.14 100th average Ask for Island 1 with separate ATC (MC 15/5).

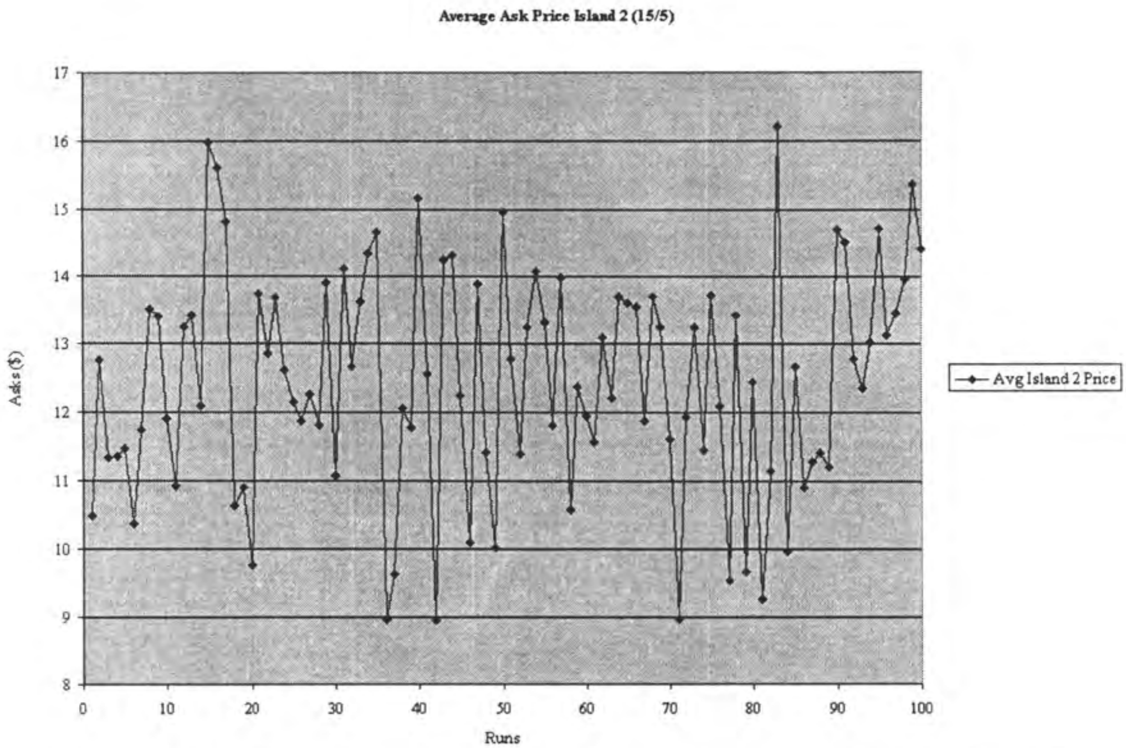

Figure 4.15 100th average Ask for Island 2 with separate ATC (MC 15/12).

Table 4.6 Market power indices for the ATC constrained networks

Full ATC 15-12	MPI	SD
All Sellers	-0.20	0.08
All Buyers	0.56	0.22
Seller [1]	-0.45	0.34
Seller [2]	-0.23	0.12
Seller [3]	-0.20	0.10
Seller [4]	-0.21	0.10
Seller [5]	-0.20	0.11
Seller [6]	-0.15	0.08
Buyer [1]	0.48	0.45
Buyer [2]	0.61	0.39
Buyer [3]	0.53	0.32
Buyer [4]	0.57	0.39
Buyer [5]	0.55	0.39
Buyer [6]	0.60	0.37

Half ATC 15-12	MPI	SD
All Sellers	-0.20	0.09
All Buyers	0.62	0.26
Seller [1]	0.10	1.91
Seller [2]	-0.21	0.25
Seller [3]	-0.19	0.11
Seller [4]	-0.19	0.11
Seller [5]	-0.22	0.13
Seller [6]	-0.17	0.13
Buyer [1]	0.44	0.47
Buyer [2]	0.54	0.34
Buyer [3]	0.56	0.45
Buyer [4]	0.68	0.47
Buyer [5]	0.92	1.26
Buyer [6]	1.73	3.95

Island ATC 15-12	MPI	SD
All Sellers	-0.27	0.09
All Buyers	0.72	0.25
Seller [1]	-0.32	0.39
Seller [2]	-0.16	0.15
Seller [3]	-0.16	0.12
Seller [4]	-0.38	0.16
Seller [5]	-0.36	0.16
Seller [6]	-0.24	0.10
Buyer [1]	0.30	0.43
Buyer [2]	0.29	0.43
Buyer [3]	0.31	0.47
Buyer [4]	1.12	0.49
Buyer [5]	1.11	0.47
Buyer [6]	1.16	0.52

Full ATC 15-5	MPI	SD
All Sellers	-0.15	0.07
All Buyers	0.39	0.21
Seller [1]	-0.19	0.31
Seller [2]	-0.16	0.26
Seller [3]	-0.21	0.34
Seller [4]	-0.13	0.09
Seller [5]	-0.15	0.09
Seller [6]	-0.13	0.09
Buyer [1]	0.36	0.52
Buyer [2]	0.34	0.48
Buyer [3]	0.42	0.57
Buyer [4]	0.36	0.47
Buyer [5]	0.46	0.53
Buyer [6]	0.37	0.45

Half ATC 15-5	MPI	SD
All Sellers	-0.16	0.07
All Buyers	0.36	0.25
Seller [1]	-0.09	1.06
Seller [2]	-0.17	0.71
Seller [3]	-0.27	0.35
Seller [4]	-0.13	0.10
Seller [5]	-0.14	0.10
Seller [6]	-0.14	0.08
Buyer [1]	0.27	0.43
Buyer [2]	0.23	0.43
Buyer [3]	0.38	0.59
Buyer [4]	0.44	0.51
Buyer [5]	0.70	1.31
Buyer [6]	0.45	1.24

Island ATC 15-5	MPI	SD
All Sellers	-0.34	0.11
All Buyers	0.98	0.35
Seller [1]	-0.05	0.31
Seller [2]	-0.06	0.35
Seller [3]	-0.04	0.31
Seller [4]	-0.41	0.15
Seller [5]	-0.40	0.14
Seller [6]	-0.40	0.15
Buyer [1]	-0.05	0.32
Buyer [2]	-0.04	0.34
Buyer [3]	-0.04	0.31
Buyer [4]	2.04	0.68
Buyer [5]	1.96	0.76
Buyer [6]	2.02	0.75

Table 4.7 Analytically derived structural market power outcomes for ATC constrained cases

15-12		15 -5	
All Sellers	-0.28	**All Sellers**	-0.07
All Buyers	0.93	**All Buyers**	0.33
Seller [1]	0.00	**Seller [1]**	0.00
Seller [2]	-0.27	**Seller [2]**	0.00
Seller [3]	-0.33	**Seller [3]**	0.00
Seller [4]	-0.33	**Seller [4]**	-0.40
Seller [5]	-0.33	**Seller [5]**	-0.40
Seller [6]	-0.40	**Seller [6]**	-0.40
Buyer [1]	0.00	**Buyer [1]**	0.00
Buyer [2]	0.60	**Buyer [2]**	0.00
Buyer [3]	1.00	**Buyer [3]**	0.00
Buyer [4]	1.00	**Buyer [4]**	2.00
Buyer [5]	1.00	**Buyer [5]**	2.00
Buyer [6]	2.00	**Buyer [6]**	2.00

CHAPTER 5. CONCLUSION AND FUTURE RESEARCH

GA Electricity Market Model

The computational agent based model using a MRE learning algorithm produced some interesting results. A few of the results seem counter intuitive. Most of them report what was expected. The RCAP and RCON measures seem inadequate to obtain the opportunities of exercising market power of the individual participates. To see this, it's necessary to take a closer inspection of the structure of the market as it relates to the behavior of the players.

Market power

As stressed by Gode and Sunder [11], it is important to distinguish between market outcomes that are due to market microstructure and market outcomes that are due to learned behavior [21]. Structural market power occurs when buyers (sellers) bid (ask) their true marginal revenue (costs) and the true demand and supply curves of the market still give some market power to a few buyers or sellers in a discriminatory auction. On the other hand, strategic market power is the misrepresenting of true reservation prices, and some buyers and/or some sellers achieve an exercisable market power in addition to differences in structural market power. As different protocols are tested for use in the deregulation of the electricity industry, knowing how alternative auction protocols affect the structural market power allocation of different market participants is extremely significant.

The structural market power results

The analytically derived structural market power results are shown in table 4.4. One interesting result is in the first two columns the buyers have a negative market power and the sellers have a positive one. They switch in the last column. It seems the sellers have a general advantage in the auction with regard to structural power market. Another interesting fact is for a given level of RCON, the average structural market power of buyers as a whole increases as RCAP increases, and the average structural market power of sellers as a whole decreases as RCAP increases. This seems counter intuitive because buyers should have a harder time exercising market power when the demand is greater than supply generated. As RCAP increases MPB should decrease while MPS increases. One last observation from the results is for each given level of RCAP, the average structural market power of buyers as a whole and for sellers as a whole are unaffected by changes in RCON. This also seems counter intuitive because only a few sellers owning all the capacity the buyers should have a hard time exerting market power over the sellers. As RCON decreases, MPB decreases while MPS should increase. As it turns out, the results in the tables from the experimental auction closely track the structural market power results. Therefore, market microstructure is a strong predictive indicator for observed market power outcomes [21].

Strategic market power

Buyers and sellers can be classified into two more types of traders. In this auction setup, some of the traders would have no chance of matching because of structural constraints. This type of trader is called extra marginal. If they are able to trade they're called infra marginal. As seen in Figure 5.1, Sellers 1,2 and Buyers 3,6 will never match if they use their true reservation prices. Since the sellers are restricted from submitting an ask below their marginal costs or buyers bidding above their marginal revenues, these players should never match.

The strategy comes into play when the infra marginal players submit prices that are matched and make more profit than competitive levels. In this auction, the traders that are structurally disadvantaged never learn how to exercise their strategic market power. This is seen in the discrepancies between the results in Tables 4.1 through 4.3 and the structural market power results in Table 4.4. Although the magnitudes are different, there are no instances in which a trader with negative structural market power achieves a positive market power level in the auction. There are only a few occasions when a trader with a positive structural market power level attains a negative market power level in the auction.

As for sign conflicts in mean market power for all buyers or all sellers, Table 4.1 has only two sign discrepancies [the MPB index for all buyers in cells (1,3) and (2,3)] and Table 4.2 has only one sign discrepancy [the MPB index for all buyers in cell (1,3)]. All these sign

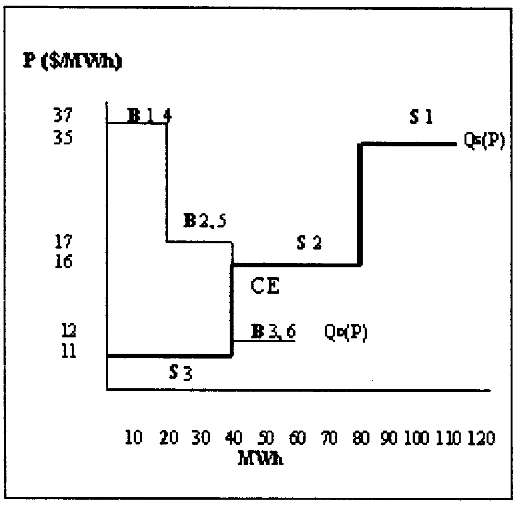

Fig. 5.1. Cell (3,1) true demand and supply curves.

discrepancies are due to (and to the disadvantage of) Buyer [1]. This Buyer's auction market power is negative while his/her potential structural market power is positive. Also, none of the mean MPB values with a sign discrepancy have an asterisk by it. As explained in a previous section, the asterisk denotes a sign change will not occur within one standard deviation.

Aside from the few sign discrepancies, learning has no effect on the strategic actions on the market powers by all traders. When all the buyers are given a greater structural market power advantage by the discriminatory auction protocol over the sellers, the buyers retain this market power in the auction experiments. The reverse is also true.

A matter of efficiency

The market efficiency (EA), previously defined, will only be 100 percent when all the infra marginal traders are trading and no extra marginal traders match. This does not mean the infra marginal traders need to make the same profits in the auction as they should in a competitive equilibrium. It only means the same amount of total profits were attained but redistributed to the different trading participants.

The highest mean EA are uniformly attained in Table 4.2. This table is from the calibrated MRE algorithm with 10,000 rounds per auction run. Table 4.2 has a mean EA of 94 percent or better. While, the 1000 round cases in Tables 4.1 and 4.3 show a generally high EA for the distinctly different settings of the MRE algorithm.

With such high EA levels, the discriminatory auction essentially becomes a zero sum game. The total profits of all buyers and sellers are given by the competitive equilibrium and redistributed among the active traders in the auction. This total profit redistribution is simply measured by the market power. When one type of trader attains a positive market power level it implies a negative market power for another trader.

Sample analysis of an interesting case

A closer analysis of the data of a cell will better explain the strategic and structural differences found in Table 4.1 through 4.4. Cell (3,1) in Table 3.3 has an RCAP and RCON equal to 1/2. The six buyers each have a capacity of 10 MWh. The three sellers have a capacity of 40 MWh. Using the marginal cost/revenue (Table 3.4) and capacity, the true demand and supply curves are constructed and shown in Figure 5.1. These curves produce a competitive equilibrium quantity of 40 MWh and a price of $14/MWh.

With a potential excess supply of electricity, the buyers should be favored in a competitive environment. It turns out that Sellers 1 and 2 have such high marginal costs ($35/MWh and $16/MWh respectively) they fail to match in the competitive equilibrium and the experimental auction. Hence they have a MPS of zero. Likewise, the lower marginal revenues of Buyers 3 and 6 prohibit them from matching in the competitive equilibrium and then also in the auction. They too have a MPB of zero as seen in Tables 4.1 through 4.4.

Seller 3, with a lower marginal cost of $11/MWh and larger supply of 40 MWh, easily matches with Buyers 1 and 4 with a marginal revenue of $37/MWh and a total demand of 20 MWh. Under the discriminatory auction midpoint price rule and using true reservation prices, this match would produce a price of $24/ MWh, exceeding the competitive price of $14/MWh. Seller 3's profit is then $260, and much larger than the competitive profit of $60. Buyers 1 and 4's profit levels are only $130, and much less than a competitive profit of $230.

Buyers 2 and 5 would then trade with the surplus supply from Seller 3 and all three traders would attain their competitive profits ($60 for Seller 3 and $30 for Buyers 2 and 5). These profits calculate a MPS for Seller 3 of 1.67 and a MPB for Buyers 1 and 4 at –0.43. Since Buyers 2 and 5 received their competitive profits, they don't perceive the market power and produce a MPB of zero.

With much of the excess supply being provided by extra marginal traders; it's literally removed from the market. Therefore, the presence of the extra marginal sellers does not provide or remove an advantage of structural market power from the other traders. The same observations were noted in the extra marginal buyers with respect to excess potential demand.

In order for the strategic market power to come into play the traders must submit adjusted reserve prices that obtain a greater profit. If the infra marginal buyers would bid $12/MWh plus some epsilon (to keep extra marginal buyers from entering the market) they would gain much larger profits and a positive MPB. Similarly, Seller 3 could submit an ask of $16/MWh minus some epsilon (again to keep out Seller 2) it would also achieve much higher profits and a MPS close to 2.5. So Seller 3 and Buyers 1, 2, 4, 5 all have potential to gain a strategic market power.

The results for cell (3,1) in all three Tables (4.1 through 4.3) is not one of the buyers successfully exercised a plan of strategic market power. The main reason for this is both the Buyers and Sellers are pushing the match prices in both directions and there is more competition on the buyers' side (4 active buyers as opposed to 1 active seller). This effect is seen in Figure 5.1. The average ask price of Seller 3 in the final auction round is roughly $15/MWh with all parameters for the MRE algorithm. This is more than Seller 3's true marginal costs of $11/MWh but lower than Seller 2's marginal cost of $16/MWh. Buyers 1 and 4 bid around $24/MWh with all MRE parameters, Lower than their true reserve price of $37/MWh but higher than the extra marginal Buyers 3 and 6's true reserve prices of $12/MWh. Buyers 2 and 5 also bid higher than Buyers 3 and 6 but lower than their true price of $17/MWh with an auction bid of $15/MWh.

Thus all active traders in this cell are trying to exercise strategic market power. The net result of the opposing forces is that Seller 3's structural market power advantage prevails in the end. The EA of this cell is high because the infra marginal traders were successful in excluding the extra marginal traders by bidding with enough caution as to not cross over the price threshold of the extra marginal trader.

Strategies of constraints

With the arrival of deregulation, the need to squeeze all the capacity out of existing transmission systems is the trend. This may be because the cost of building new transmission line without knowing exactly how the return on such an investment will be recovered is just a little too high and risky. As new electricity systems use a clearinghouse mechanism to buy and sell electricity, ATC shortages will cause the system some distress. As demonstrated in some deregulated states, constrained transmission systems can have a vast impact not only to the supply of energy, but by the price of the electricity as well. These constraints were simulated using the GA MRE auction to see what happens to the market power and prices in a gradually constrained system.

The marginal costs for the sellers are shown in Table 3.5. The ATCs of the semi separated and fully separated grids are presented in Tables 3.6 and 3.7. Sellers 3 and 4 are chosen for closer study because they are located on the border between the two zones of ATC separation. Figures 4.6 through 4.11 display the asks submitted by Sellers3 and 4 in the last round of 100 runs. A more careful analysis of the gradually decreasing marginal cost sellers will be done first.

The sellers with marginal cost of 15, 12, 10, 10, 10, and 5 were tested in the three different ATC arrangements shown in Tables 3.6 and 3.7. Figure 4.9 shows the unconstrained asks of Sellers 3 and 4, each having a marginal cost of \$10/MWh. In the auction, Seller 3 has the average ask of \$13.2/MWh. This isn't far from the structural midpoint between the Buyers bid of \$20/MWh and when Seller 3 asks of \$10/MWh. Seller 4 having of the same marginal cost as Seller 3, produces about the same average bid of \$13.3/MWh. Figure 4.7 shows a great deal of fluctuation of the asks. The Seller doesn't seem to be able to find a single profit maximizing ask. The average asks of these two sellers are lower than the structural midpoint of the next highest Seller (\$16/MWh) and their own midpoint of \$15/MWh. As for semi-constrained ATC in Figure 4.9, the asks seem to be more consistent but still have an average of around \$13.7/MWh. The major difference in average asks is found in the fully separated islands seen in Figure 4.10. In this figure, Seller 4's asks on average are below Seller 3's asks. Island 2 (lower right or Seller 4's island) is required to submit prices against a competitor with the same marginal cost and one with much lower marginal costs. Thus, forcing Seller 4 to lower his asks to just above the structural midpoint (\$12.5/MWh) of the cheapest seller. While Seller 3 can still enjoy a comfortable average ask of \$13.9/MWh, as one of the cheaper sellers in Island 1. The average island prices, over the 100 runs, are shown in Figures 4.12 and 4.13. The average asks of Sellers 3 and 4 are similar to Island 1 and 2's averages of \$15.7/MWh and \$12.5/MWh respectively. This would suggest the two sellers are bidding close to the island price and trying to gain some sort of strategic market power.

The second constrained experiment dealt with the sellers' marginal costs starting out being quite different (15,5) as seen it Table 3.5. This was designed to observe what happened when there was going to be two distinct island prices. Figure 4.6 shows the last round of asks for Seller 3 (MC = 15) and Seller 4 (MC = 5). The asks are much more stable with less competitors and different pricing schemes to counteract. The average unconstrained ATC ask for Seller 3 is $17.3/MWh and the discriminatory midpoint is $17.5/MWh. Seller 4's average ask is $12.4/MWh and a discriminatory midpoint of $12.5/MWh. There is still a strong correlation between the structural market power and auction results as explained earlier. When the ATCs are slightly restricted as per Table 3.6, the average asks stay about the same ($16.7/MWh for Seller 3 and $12.7/MWh for Seller 4). Apparently the sellers have already found out how to trade without the constraints affecting them too much. Finally, the separate islands show a very settled ask pattern seen in Figure 4.11. Totally isolated from extraneous marginal costs, the Sellers 3 and 4 obtained average asks of $17.0/MWh and $9.7/MWh respectively. Both are submitting prices below their structural midpoint prices. When the two islands are isolated through the reduction in ATC and the true reserve prices of an island are identical, all buyers and sellers have no analytically derived structural market power. They are already at their competitive equilibrium prices. Island averages shown in figures 4.14 and 4.15 produces overall averages of 16.9 for Island 1 and 9.6 for Island 2. These averages are similar to the individual sellers' average asks. As already observed, the correlation between the structural tendencies and the auction outcomes are certainly positive.

MPI of constrained ATC

The market power indices are shown in Table 4.6. The top half are the results of the Sellers having a marginal cost of 15,12,10...etc. In Table 4.7 the analytically derived structural market powers are displayed. The sellers at full ATC start out obtaining a market power close to their structural market power. Sellers 4, 5, and 6 lose some MPS as the ATC becomes more constrained. But they are definitely the same sign as structural market power suggests. Consequently their counterpart of Buyers (4,5,6), gain MPB up to 1.12, 1.11, and 1.16 respectively. These MPBs are almost exactly what they should be according to the structural market power. Again this confirms the strong tendencies of structural market power on the market power gained in the auction. Buyer and Seller 1 have a structural market power of zero but end up with market powers ranging from 0.48 to 0.43 and -0.45 to 0.10 respectively. The standard deviation of Buyer 1's and Seller 1's MPI is usually larger than the MPIs themselves. The MPI are within the range of zero.

The lower half of Table 4.6 reports the MPI for the case where the sellers have a marginal cost of 15 and 5. With two islands of prices already introduced into the network, the dramatic change in market power doesn't appear until two separated islands exist. The islands give Sellers 1, 2, and 3 a boost in market power (less negative), while Seller 4, 5, and 6 drop in market power. The analytical structural market power for Sellers 1, 2, and 3 is zero. As the system is constrained, then auction market power attained by these sellers are very small negative numbers with standard deviations easily setting them near zero. The remaining Sellers (4,5,6) move closer to their structural market power of –0.4 as the ATC is congested to separate islands. It seems strange that the sellers reach their analytically derived structural market power levels when there is no structural market power to be obtained with two separate islands of transmission.

The analytical structural power for Buyers 1, 2, and 3 is zero. With an unconstrained system, they have a moderately large MPI, ranging between 0.34 and 0.42. This diminishes to a very small negative MPI as the ATC islands. The remaining Buyers (4,5,6) derive a structural market power of 2. Again, as reported in Table 4.18, they obtain this as the ATC is constrained to separate islands.

There are many possible explanations of the island structural market power results. All the buyers and sellers are still in the same auction and are bidding the strategies that maximize profits even if it's only with their island counterparts. When the islands are formed, competitive equilibrium becomes the rule of discriminatory pricing and tends to favor the generic buyers pressure of structural market power. When the grids have full ATC, the structural market power influences the sign (positive or negative) of the MPIs. Even as the system congests, the structural tendencies strengthen. When the totally isolated islands of transmission are created the structural market power dominates the MPIs. Strategic market power has a harder time of being exercised as both buyers and sellers battle each other over profit redistribution. To think of it in another way, they strategize to exploit their structural market power.

The Value of Information

The agents in the auction quickly learned where they can bid and where they lose in the matching process. This is real time information for them. They learn where the approximate reserve prices are or they don't last. The value of this kind of information is extremely high to a market participant. If they have models of the other participants they won't need to waste time and resources trying to find the reserve prices of the other players. In the auction experiments, the structural market power of the players played a large role in how the players split up the profits. Knowing this is a huge advantage and can be applied to strategize long-term profit maximizing plans.

Energy traders need both long and short term strategies to successfully compete in the changing deregulated environment. Many fatcors must be considered in order to develop such strategies. The use of computational auction models, forecasting, and certain types of analysis are crucial to making tough decisions, which have lasting consequences. The value of the extra information found through research can be calculated. Then the maximum amount of resources to be used in the information discovery should be employed to come out ahead. One approach is to develop a comprehensive combination of the techniques in one simulator to provide a practical guide to the circumstances at hand.

A Proposed Approach

A good place to begin for the electricity industry strategies is predicting the status of the transmission system. This means not only the demand and supply of the grid area but the potential constraints (i.e., congestion, outages, etc.) on this system. The load forecasting can be done using an ANN. These are in use and have proven to be very accurate in STLF (see Chapters III, IV). Continual improvements in the design and training (see Chapter II) of ANN will extend the range of the accurate forecasting. Longer range forecasting can be made with ANN and expert rules with specific knowledge about the system in order to adjust for inaccuracies in the outcomes. With the load forecasts and their corresponding probability distributions in hand, they can be used in a computational auction as the ATC or quantity bids of the other players. This computational auction would have to be programmed with the same protocols employed by the relevant power exchange. As previously demonstrated, the differences in protocols have a major impact on the structural advantages of the auction. The auction simulator should have updated running models of the known power exchange participants. These models could include cost and revenue curves along with physical capabilities of the companies. Each player would have a learning algorithm similar to the MRE but with a set of strategies specifically chosen for the player and the ability to make drastic increases (no upper limit on the sellers' asks). The auction would be run for thousands of rounds and hundreds of runs to approximate the price for electricity during that hour, day, or some specific time period. Once the expected behavior of the other players is approximated and a price is discovered, strategies of how to outbid the other players or make as much profit as possible are conceivable. The auction simulator should be started again to see if the players act differently. Then the final price and associated probability distribution can be integrated into a decision tree (see Chapter II) for analysis with other opportunities presented to the company. Other real options may be available that could be more beneficial at that point in time and need to be considered.

With the decision tree analysis, a risk analysis is required to show the true value of the decisions. Risks would include, but not limited to realistic probabilities of: price swings, power outages, changes in laws, and changes in stock market values. Naturally a company wants to minimize the risk as much as possible. Hedging risk (see Chapter II) is a very smart and common way to reduce the amount of risk a company is exposed. Futures contracts on electricity are already traded on commodity exchanges. Futures and options should be utilized to reduce this risk. For example, through the careful modeling of transmission grid, an energy company predicts congestion in a certain area of the grid serviced by a few companies. Knowing this they can buy electricity futures contracts from the other suppliers in the area and then resell the power at the specified time, hopefully when the prices increase. Another strategy would be to take a position in a long call option (see Figure 2.7). When the spot price increases, the company exercises the option and buys electricity from the contract holder at the lower strike price and sells it on the open market for a profit. If the spot price never increases as predicted, the company would simply not exercise the option and only lose the premium they paid for it. Many methods of risk analysis and option pricing exist for such hedging.

The decision tree analysis can be finished and appropriate strategies can be implemented. The energy traders will use a much quicker analysis of the system's status for next hour pricing. But long term trading should use similar techniques to solve multiple decisions for the company's best interest.

Determining the value of the certain information can simplify some of the analysis by using concentrating on the most cost effective research. For example, peaking hours of the day for electricity load have much higher associated costs and prices. By concentrating on accurately forecasting these hours more so than the off peak hours will produce more cost effective results. The money saved or earned during the peak hours can outweigh the off peak hours.

In summary, it was shown for an auction with certain protocols structural market power has a strong influence over the market power if the individual agents. Even when the ATCs are constrained the structural market power will impact the market power of a player.

This is unique knowledge that can be utilized in company strategies. Forecasting the status of the system is necessary for long term planning. Also having a computation model of the auction and other players can be used to predict the market price. With market conditions and prices, a comprehensive risk and decision analysis can be developed to maximize company profits and minimize risk for the future health and welfare of the next generation of energy companies.

GLOSSARY

ANN – Artificial Neural Networks

ARIMA – Auto Regressive Integrated Moving Averages

ARMA – Auto Regressive Moving Average

ART – Adaptive Resonance Theory

ATC – Available Transmission Capacity

CB – Capacity of the Buyer

CBOT – Chicago Board of Trade

CDF – Cumulative Distribution Function

CE – Competitive Equilibrium

CS – Capacity of the Seller

DHT – Discrete Hartley Transform

EA – Efficiency

ESCO – Energy Service Company

FFT – Fast Fourier Transform

FHT – Fast Hartley Transform

FT – Fourier Transform

GA – Genetic Algorithm

GENCO – Generation Company

HT – Hartley Transform

ICA – Independent Contract Administrator

ISO – Independent System Operator

MPB – Marginal Price of the Buyer

MPI – Market Power Indicator

MPS – Marginal Price of the Seller

MR – Marginal Revenue

MRE – Modified Roth Erev

MW – Megawatts

MWh – Megawatts per hour

NB – Number of Buyers

NN – Neural Networks

NS – Number of Sellers

NYMEX – New York Mercantile Exchange

P – Profit

PBA – Profit of the buyer in the Auction

PBCE – Profit of the Buyer in Competitive Equilibrium

PDF – Probability Distribution Function

PSA – Profit of the Seller in the Auction

PSCE – Profit of the Seller in Competitive Equilibrium

Q – Quantity

RCAP – Relative Capacity of buyers (sellers)

RCON – Relative Concentration of buyers (sellers)

RE – Roth Erev

RMSE – Root Mean Squared Error

RTO – Regional Transmission Operator

SG – Stacked Generalizations

SOM – Self Organizing Maps

STLF – Short Term Load Forecasting

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